Master's Thesis

Identifying patterns of mergers and acquisitions at the industry level

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Abstract

The existing studies on mergers and acquisitions (M&A) have mainly focused on firm's technological capabilities based on patent analysis. Therefore, they have not considered the evolutionary and industry-level aspects of M&A to support M&A decision making. To counter this, we propose a systematic approach to identifying patterns of M&A at the industry level on the basis of the change of historical M&A transactions. For this, first, historical M&A transaction data providing industry information to which firms belonged on the transaction date from Securities Data Company (SDC) platinum database is collected at regularly spaced interval of time. Second, Association Rule Mining (ARM) is modified to take into account a direction of M&A transaction to extract significant M&A transaction rules of which indices are greater than the cut-off value. Third, network analysis is conducted to construct an M&A transaction relationship network and to measure six quantitative indicators for confirmation of characteristics of industry and significant M&A transaction rules via the concept of degree centrality. Finally, significant M&A transaction rules are categorized into dynamic and structural patterns of M&A using indicator analysis and cluster analysis respectively to identify the evolution of trend in M&A transactions. Our empirical analysis employs a total of 71,264 M&A transactions data from 1995 to 2016, and enables practitioner to obtain not only the specific industry information but various in M&A patterns for establishing M&A implementation strategies at the industry level. We expect that the proposed approach will be effective as complementary tool for M&A decision making where corporations determine a principal screening or selection criteria to shorten monetary and time cost for searching candidates as target industry.

Keywords: mergers and acquisitions, dynamic patterns of M&A, structural patterns of M&A, characteristics of industries, network analysis.

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1. Introduction

A strategic importance of M&A in corporation have been increasing. In 2016, corporation spent over $3.7 trillion on M&A globally with the majority trend that M&A transactions are actively being carried out not only between related industries but unrelated industries (Thomson reuters, 2016). However, many M&A activities remain unsuccessful. Corresponding to this issue, identifying the factors which affect the success of M&A and development of M&A decision support have been an attractive area for academic research.

In this regard, M&A has been the central issue of finance, strategic management, and organizational behavior (Fowler et al, 1989; Agrawal et al, 1992; Paul et al, 1992; Stefano and Volpin, 2004). In terms of the conceptualization of phenomenon in M&A, these studies provide valuable information on the basis of various managerial theories, but they may not be appropriate for direct support tool for M&A decision. In order to overcome the above limitations, some studies in the technology management field have proposed a quantitative approach to support M&A decision making using technology information such as suggestion of M&A target candidates based on patent citation analysis (Breizman and Thomas, 2016), prediction of M&A via ensemble learning with patent information (Wei et al. 2008), evaluation of the target corporation's technical strength and market value by means of patent analysis (Breizman et al. 2000), integration of technology for M&A decision making (James et al. 1998), and an evaluation of the corporate M&A strategy (Park et al. 2013). These studies have employed the patent data collected from the United States Patent and Trademark Office (USPTO) database. It is regarded as the proxy for technology since patent data provides technological information, both general and detailed. In this way, Granstrand et al. (1997), Narin (1987), and Patel and Pavitt (1997) proved that patent data is adequate when representing a firm's technology capability and these studies strengthened the reliability of the quantitative approach. Even though these studies have suggested quite useful approaches to supporting M&A decision making aimed at reinforcing firm's technological competitive advantage (e.g. acquisition of cutting-edge technology and high quality researcher), they provide the limited information in M&A search process. Because patent data only cover the technological information. These shortcomings necessitate the development of a new approach for strategic M&A decision making to cope with the recent M&A trend trends that are actively merging among unrelated-industries. In this study, we develop the exploratory and industry-level approach considering following three conditions.

First, in terms of data, it should be possible to be analyzed at the industry level, in order to provide information from a macroscopic point of view on M&A. Individual pieces of data should be clearly classified to the industry level describing in detail the business, and should indicate the industry to which the enterprise was belonging on the transaction date. The industry-level analysis provides that corporations can observe and record the whole M&A trend to identify which industries are key players in M&A and which industries strongly form transaction relationships. Second, with respect to research findings, we focus on the patterns of M&A as time passed. Identifying patterns of M&A is an exploratory approach that can analyze the historical M&A activities and reflect market conditions regarding M&A strategies. Establishing an M&A strategy by identifying historical M&A activities is a low-risk strategy in the way that it provides a specific direction of M&A on the basis on completed M&A transactions. In addition, this study provides detailed information on changes in M&A trends among interested industries by confirming changes in these patterns of M&A as time passes. Finally, from a practical standpoint, data visualization and the development of quantitative indices are required to understand patterns of M&A more intuitively. These aids help practitioners to rely less on experts-knowledge.

Considering above conditions, in this study, we propose a systematic and exploratory approach to identifying the patterns of M&A at the industry level. The tenet of this study is that significant patterns of M&A extracted from large quantitative databases can provides valuable information on the evolution of trend of M&A to make M&A decisions where corporations determine a principal screening or selection criteria in the search process.

The proposed approach is performed by the following sequence. (1) data collection of historical M&A transaction data providing industry information to which firms belonged on the transaction date from SDC (Securities Data Company) platinum M&A database; (2) extraction of significant M&A transactions via a modified association rule mining by considering the direction of M&A transaction; (3) generation of a M&A transaction network for data visualization and the discovery of industry characteristics using network analysis based on the concept of in/out degree centrality; and finally (4) identification of the dynamic and structural patterns of M&A by using change of two quantitative indicators between time periods, and cluster analysis respectively.

The remainder of this paper is organized as follows. A related work of previous studies on M&A are presented in the second section. The research framework is explained in the third section. An empirical analysis is delivered in the fourth section. Finally, the fifth section offers our conclusions.

2. Related work

Previous studies on M&A

M&A is generally defined as transactions where a corporation trades the assets of a company or companies, which is used as a major management strategy to achieve various managerial objectives, such as increasing the market share, promoting economies of scale, or early-entering new businesses. In academia, M&A has been a central issues in the various fields to conceptualize the phenomenon in M&A process. In this section, we review the previous studies in three main areas- finance, strategic management, and organization behavior- in which M&A research has been conducted.

First, many financial researchers have mainly concentrated on the issue of whether M&A is a wealth creating event for shareholders or not. Research has predominantly used stock prices to evaluate shareholder wealth, because they are the direct and acceptable measure of stockholder value. (Campa and Hernando, 2004; Lubatkin and Shrieves, 1986). The main researches to clarify this are as follows. Datta et al (1992) identified the influential factor on shareholder wealth creation in mergers and acquisitions using a total of 41 studies with a total of 209 usable observations. They investigated that while the target firm's shareholders gain significantly from mergers and acquisitions, those of the bidding firm do not. Moeller et al (2005) found that acquirer shareholders lost 12cents per dollar spent on acquisitions for a total loss of $240billion from 1998 to 2001. The aggregate dollar loss of acquiring-firm shareholders was so large from 1998 to 2001, because there were a small number of acquisitions with negative performance by firms with extremely high valuations. Researches in specific industry fields are also actively conducted, Cybo-Ottone and Murgia (2000) studied about stock market valuation effects of M&A in 14 institutions in the EU banking industry. They employed a sample of very large deals from 1988 to 1997 and found that the value for the average merger increased significantly on the deal's announcement date. However, M&A with securities firms and concluded with foreign institutions did not gain a positive market's expectation.

Second, M&A research in the strategic management field has studied M&A from various perspectives such as goal of M&A, identification of post-merger performance, and integration of M&A (JB Kusewitt, 1985; DK Datta, 1991; L.Capron, 1999; DR King et al. 2004;). The managerial goals of M&A are to utilize the target firms' expertize in production, marketing, or other areas within the acquirer, to reduce risks and costs of diversifying products and services, and to penetrate new markets by utilizing the target firms' marketing capabilities (). The literature of 'strategic fit' has been interested in the association between firm performance and the strategic attributes. Schiereck et al (2004) found that less active bidders create more value compared to more active and experienced bidders and Cuypers et al (2016) examined the role of the acquirer's and target's experience when the value of M&A is created. They found that the value obtained is an outcome of a distributive process in which both the acquirer and target play an active role, such that differential experience is a key determinant of which one obtains how much value. In terms of integration of M&A, various management consulting corporations have performed empirical studies of M&A integration (Fujitsu Consulting, 2001; Mercer Management Consulting, 1997; Price Waterhouse Coopers, 2000). These studies proved that the speed of the integration of M&A may be positively related to success. Homburg and Bucerius (2006) studied the benefit and determinant related to the speed of integration of M&A. The speed of integration has a strong relationship with M&A success in the case of low external and high internal relatedness, while the impact is strongly negative the high external and low internal relatedness. Hagedoorn (2002) studied the preference either strategic technology alliance or M&A when firms take advantage of external sources. This study shows that if the external sourcing of innovative capabilities comes closer to the core business of a company, the role of integration becomes more important because in that case M&A provides greater control than strategic technology alliances.

Finally, much of the extensive organization behavior literature on M&A mainly have focused on the cultural fit and behavioral responses of the employees involved. Especially, the relationship between culture and performance has attracted research attention. Studies examining this relationship employed cultural distance to measure cultural differences, both domestic and cross border. One group suggests that there is a negative link between cultural distance and M&A performance (Buono et al, 1985; Stahl and Voigt, 2005). Another group assert that the relationship between cultural distance and M&A performance is positive (Morosini et al, 1998; Chakrabarti et al, 2009). There is no academic consensus because the results are slightly different according to which indicator was as input. Chakrabarti et al (2005) proved that if the acquirer and target firms come from countries that are culturally disparate, post-merger performance is better in the long-run. Ahammad et al (2014) highlighted that organizational culture differences affect negative influence on mediate relationships between knowledge transfer and cross-border acquisitions performance. Furthermore, Vaara et al (2014) found that prior experience strengthens the association of M&A failure with cultural differences. It means that cultural differences may deliver a convenient attribution target for less successful M&A performance.

3. Data and Methodology

3.1. Data

SDC platinum database is the data source of this study. This database allows us to identify comparable transactions, monitor markets and industries, and prospect for new business because it provides various and detailed financial information on global new issues, M&A, industry specific, corporate governance, global public finance, and securities trades (SDC user guide, 1999). Among others, we chose to base our research on SDC platinum M&A data to identify patterns of M&A. SDC Platinum M&A data have been used in various M&A studies and have the following advantages. First, SDC Platinum M&A data is reliable. Fuller et al (2002) verified the announcement dates in a random sample of 500 SDC deals and found them to be correct in more than 90% of the cases. SDC Platinum M&A data has no information distortion since SDC Platinum M&A data is directly gathered from United States Securities and Exchange Commission (U.S SEC) and foreign equivalents, direct surveys of advisor institutions, trade press publications and company press releases. Second, SDC Platinum M&A data is large-scale and provides various M&A information. It covers over one million worldwide M&A transactions since the 1970s in electronic format. Its' database also performs a daily update and highlights over 1400 data elements including target and acquirer profiles, deal terms, deal value and stock premiums.

3.2. Methodology

This section examines the overall process, giving a brief explanation of each stage. The proposed approach is comprised of four steps as shown in Fig. 1. The proposed approach employs various methods such as modified association rule mining, network analysis, and the cluster analysis to discover dynamic patterns of M&A. As the involvement of many methods and complex algorithms may lead to conceptual misunderstanding and imprecise use in practice, the proposed approach is designed to be executed in four discrete steps: First, historical M&A data providing industry information to which firms belonged on the transaction date is collected from SDC platinum database at regularly spaced interval of time Second, association rule mining is modified considering the direction of M&A transactions to extract significant M&A transaction rules of which indices are greater than the cut-off value in a time period. Third, network analysis is conducted to construct an M&A transaction relationship network and to measure six quantitative indicators for confirmation of characteristics of industry and significant M&A transaction rules via the concept of degree centrality. Finally, significant M&A transaction rules are categorized into dynamic and structural patterns of

M&A using indicator analysis and cluster analysis respectively to identify the evolution of trend in M&A transactions.

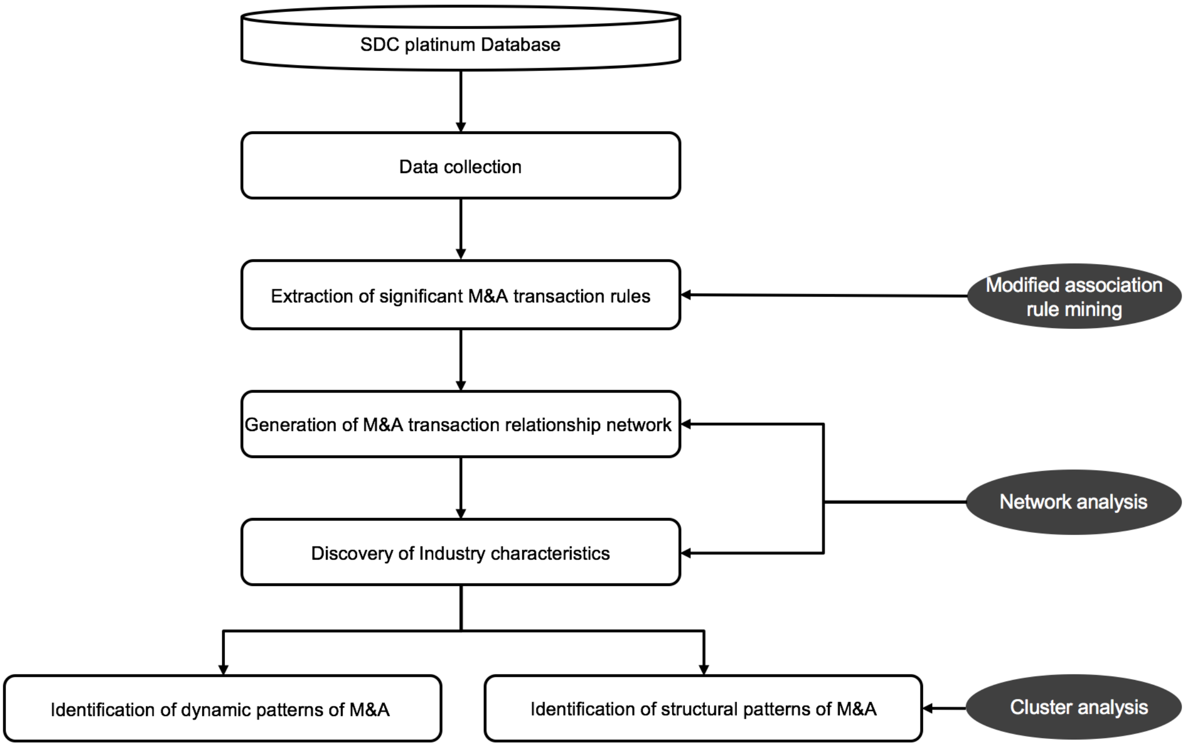

Figure 1. Overall process of the proposed approach

3.2.1. Modified association rule mining

Association rule mining is a rule-based data mining technique that discovers significant relationships among items from a given data set (Agrawal et al, 1993). Discovering association rules is widely used in marketing and it is sometimes called "market basket analysis". It generates association rules X → Y which indicate “what goes with what”, for instance customers who bought item X also bought item Y. X and Y are called ‘antecedent’ and ‘consequent’.

There are three major measurements for association rules X → Y as follow. Firstly, support X → Y is defined as the ratio of the number of transactions that include both items X and Y against the total number of transactions. It means that the support value of rule X → Y is the probability of co-occurrence of item X and item Y in a whole database. Secondly, confidence X → Y is the ratio of the number of transactions containing item Y among transactions containing item X. It can be interpreted as the estimate of the conditional probability P (Y|X). Finally, lift X → Y is calculated by dividing the confidence by the probability of occurrence of item Y. This indicator shows the statistical dependence between items X and Y.

However, association rule mining cannot be directly applied where input data already has direction (e.g. M&A, investment, corporate governance). It means that 'antecedent' and 'consequent' are fixed as they represent the acquiring and target corporation respectively in each M&A transaction. Accordingly, we modified the association rule mining as summarized below. We redefined the major measures in this study and extracted the significant M&A transactions which were higher than a prescribed cut-off value. For accessible understanding, the following major indices assume X for the antecedent and Y for the consequence.

(1) $Support_{ac}(X)$: The number of Industry X as acquirer divided by total number of M&A transactions. The high value of $Support_{ac}(X)$ implies that the companies within the Industry X frequently appears as acquirer in overall M&A transaction dataset.

$$Support_{ac}(X) = \frac{N_{ac}(X)}{N(T)}$$

Where $N(T)$ is the number of whole M&A transactions, and $N_{ac}(X)$ is the number of Industry X as acquirer.

(2) $Support_{ta}(\mathrm{Y})$: The number of Industry Y as target divided by total number of transactions. The high value of $Support_{ta}(\mathrm{Y})$ implies that companies within the Industry Y frequently appear as target in overall M&A transaction dataset.

$$Support_{ta}(\mathrm{Y}) = \frac{N_{ta}(Y)}{N(T)}$$

Where $N_{ta}(Y)$ is the number of Industry Y as target.

(3) $\mathrm{Support}_{ac\rightarrow \mathrm{ta}}(\mathrm{X} \rightarrow \mathrm{Y})$: The number of M&A transactions, which is acquirer and target are Industry X and Industry Y, in dataset. The high value of $\mathrm{Support}_{ac\rightarrow \mathrm{ta}}(\mathrm{X} \rightarrow \mathrm{Y})$ implies that companies within the Industry X frequently merge with companies within the Industry Y in overall M&A transaction dataset.

$$Support_{ac\rightarrow \mathrm{ta}}(X \rightarrow Y) = \frac{N_{ac\rightarrow ta}(X \rightarrow \mathrm{Y})}{N(T)}$$

Where $N_{ac\rightarrow ta}(X \rightarrow \mathrm{Y})$ is the number of transactions in which Industry X and Industry Y are acquirer and target.

(4) $Confidence_{ac\to ta}(X \to Y)$: The number of transactions containing Industry Y as target among the transactions containing Industry X as acquirer. The high value of $\mathrm{Confidence}_{ac\to ta}(\mathrm{X} \to \mathrm{Y})$ implies that companies within Industry X merge with companies within Industry Y with high probability among M&A transactions that companies within Industry X are the acquirer.

$$\mathrm{Confidence}_{ac\to ta}(\mathrm{X} \to \mathrm{Y}) = \frac{Support_{ac\to \mathrm{ta}}(X \to Y)}{Support_{ac}(X)}$$

(5) $Lift_{ac\to ta}(\mathrm{X} \to \mathrm{Y})$: The ratio of $\mathrm{Confidence}_{ac\to ta}(\mathrm{X} \to \mathrm{Y})$ to $Support_{ta}(\mathrm{Y})$. The high value of $Lift_{ac\to ta}(\mathrm{X} \to \mathrm{Y})$ implies that companies within Industry X as acquirer and companies within Industry Y as target are dependent on one another.

$$Lift_{ac\to ta}(\mathrm{X} \to \mathrm{Y}) = \frac{Support_{ac\to \mathrm{ta}}(X \to Y)}{Support_{ac}(X) \times Support_{ta}(\mathrm{Y})}$$

3.2.2. Network analysis

Network analysis is a method that analyzes network structures quantitatively by forming relationships between data objects. It characterizes networked structures in terms of nodes and links that connect those nodes. Network analysis is widely used in various fields such as sociology, biology, and information systems, since a network is a general method yet a powerful means of representing patterns of connections or interactions between the parts of system (Newman, 2016).

In this study, we constructed an M&A transaction network based on significant M&A transactions extracted from modified association rule mining. Node and link means industry and relationship of M&A transaction respectively and network analysis was employed due to the following advantages. First, data visualization, one of the key elements of network analysis, enabled us to instantly identify the important structural characteristics of given network that are difficult to capture in raw data. In this point, it is easy not only to identify the structure of M&A by displaying the size of nodes and thickness of edges of particular patterns but to compare them by visualizing the network for a certain period of time. Second, there are various kinds of measures (e.g. bridge, centrality, density) that quantify the characteristics of each nodes. These measures allow researchers to classify and rank individual nodes according to their own criteria. We employed the degree centrality which is defined as the number of links that a node has. In the case of a directed network (i.e. where links have direction), the degree centrality is measured by dividing it into two different concepts, in-degree and out-degree centrality. In-degree is a count of the number of links directed to the node and out-degree is the number of links that the node directs to others. In-degree is often interpreted as a form of popularity, and out-degree as gregariousness. In this study, six quantitative indices that express the characteristics of a node were calculated by changing the value of the link based on the concept of in-degree and out-degree centrality.

In our network, the size of a node and the size of node label represents the degree-centrality,

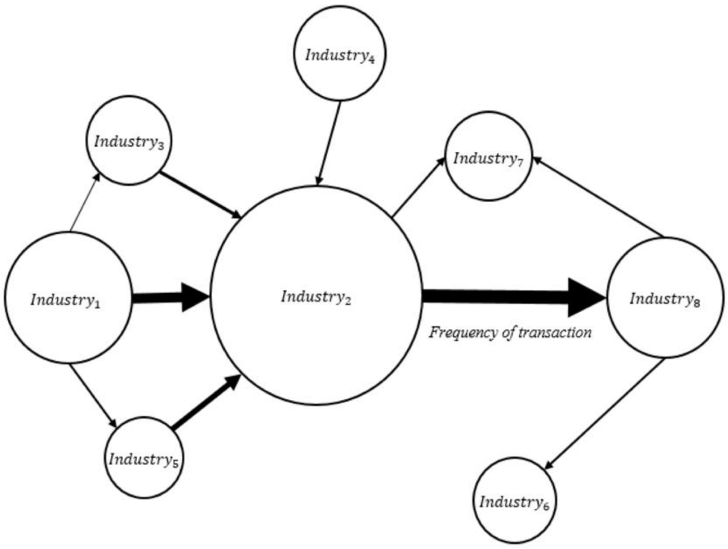

Figure 2. Example of M&A transaction network
(The value of link: the frequency of a given transaction)

and the thickness of the link represents the frequency of a given transaction, the confidence value of a given transaction, and the mean of the deal value of a given transaction. For a clear understanding, the network example according to each link value is as shown in Fig. 2, Fig. 3, Fig. 4 and the indices measured according to the change of link value are defined as follows.

(1) *The degree of acquirer*: This is the index that represents the number of appearance as the acquirer within the network. It is calculated as the sum of the values of each link from the given node to neighboring nodes. In terms of *Industry2*, the degree of acquirer is measured by summing the value of links heading to *Industry7*, *Industry8.*

(2) *The degree of target*: This is the index that represents the number of appearance as the target within network. It is calculated as the sum of the values of each link from the neighboring nodes to the given node. In terms of *Industry2*, the degree of acquirer is measured by summing the value of links entering from *Industry1*, *Industry3, Industry4, and Industry5.*

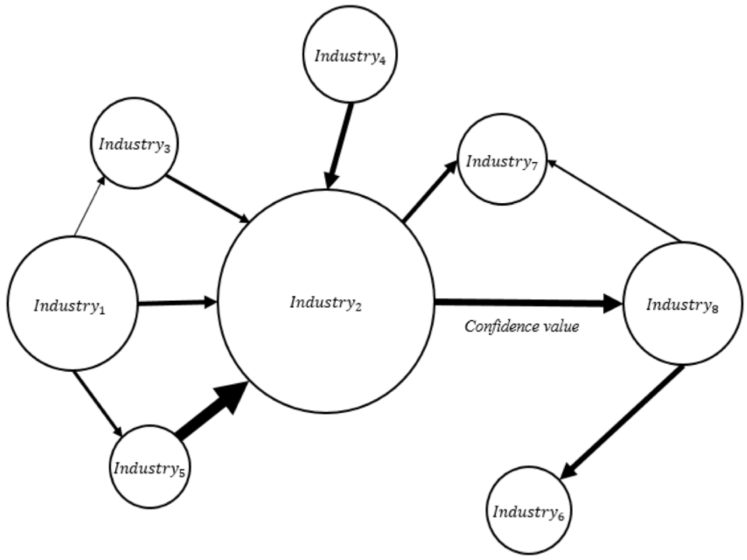

Figure 3. Example of M&A transaction network
(The value of link: the confidence value of a given transaction)

(3) *The degree of merge-diversity*: This is the index that represents the number of industries with which acquirer merge within network. It is calculated based on out-degree centrality. In terms of *Industry2*, *The degree of merge-diversity* is two.

(4) *The degree of merged-diversity*: This is the index that represents the number of industries that merge with given industry, as target, within network. It is calculated based on in-

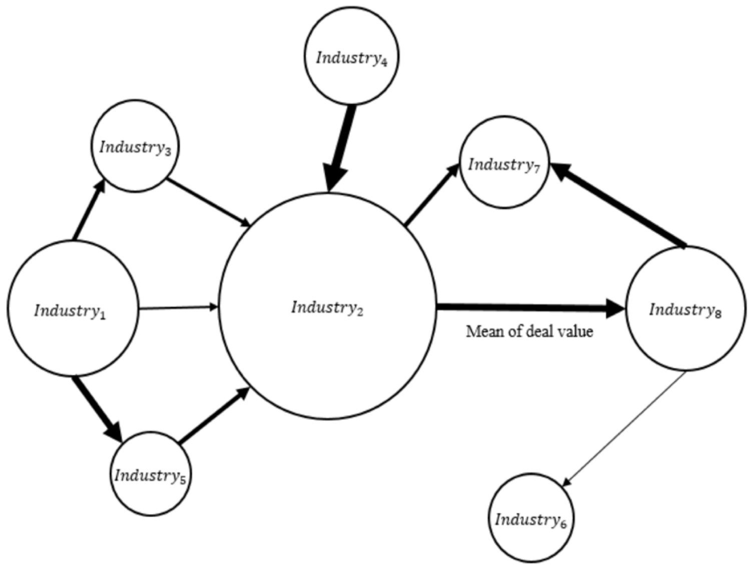

Figure 4. Example of M&A transaction network
(The value of link: the mean of deal value of a given transaction)

degree centrality. In terms of *Industry2*, *The degree of merged-diversity* is four.

(5) *Average-invest deal value*: This is the index that represents the mean of the deal value invested by the given industry into the target industry within the network. It is calculated as the sum of the values of each link from the given node to neighborhood nodes. In terms of *Industry2*, *Average-invest deal value* is measured by summing the value of links heading to *Industry7*, *Industry8.*

(6) *Average-invested deal value*: This is the index that represents the mean of the deal value invested by the acquirer industry into the given industry within the network. It is calculated as the sum of the values of each link from the neighborhood nodes to the given node. In terms of *Industry2*, *Average-invested deal value* is measured by summing the value of links entering from *Industry1, Industry3, Industry4, and Industry5.*

Finally, we organized the table of industry characteristics which is comprised of the six indices above.

3.2.3. Cluster analysis

The cluster analysis is an unsupervised data mining technique. It is an exploratory analytical method used to understand the structure of an entire dataset by grouping objects with similar properties among several individuals into specific groups and then identifying the characteristics of each group. Cluster analysis is widely employed in various research fields. For example, in marketing, market segmentation that divides a consumer or business market based on demographic and market data is performed via cluster analysis (Green et al, 1967; Sounders, 1980; Shim and Bickle, 1994).

This study takes advantage of a K-means cluster algorithm to identify the structural patterns of M&A by using indices of industry characteristics measured by network analysis and major indices of modified association rule mining as the input. We identified structural patterns of M&A with similar characteristics in each period and confirmed a difference to the characteristics of M&A transactions belonging to individual clusters. The K-means cluster algorithm is a method generally used to automatically partition a data set into K groups (Mac Queen, 1967). It aims to partition the number of N observations into the number of K clusters in which each observation belongs to the cluster with the nearest mean. The K-means cluster algorithm determines the sum of the squares of the distances between the centroid of each group and the data objects in the group as a cost function and it achieves cluster analysis by updating the group that each object belongs to, in a way that minimizes the value of the function. The formula for minimizing the cost function is as follows.

$$argmin_S \sum_{i=1}^{K} \sum_{x \in S_i} \|x - \mu_i\|^2$$

Given a set of observations $x_1, x_2, x_3, \ldots, x_n$, where each observation is a d-dimensional real vector, the K-means algorithm has an intention to partition the n observation into $K(\leq n)$ sets $S = \{S_1, S_2, \ldots, S_K\}$. μ_i is the central point of the cluster i. In this process, the similarity between data entities in the same cluster is maximized, and the similarity between the clusters is minimized. The process is performed according to the following sequence. First, an arbitrary number of K clusters are determined, and a cluster center is assigned to each cluster to set the position. Second, for each piece of data, calculate the distance to each cluster centroids and placed in the closest cluster using Euclidean distance. Third, the center of the new cluster is reassigned to the minimum on the basis of data divided into clusters. Finally, if the location of the center of the newly decided cluster is the same as the existing one, the algorithm ends, but if not, the process from second step is reiterated. In this process, the similarity between the data objects in the same group increases, and the similarity between groups decreases.

4. Empirical analysis and results

4.1. Data

We collected our M&A transaction sample from the SDC Platinum database using the following relevant search conditions. Data on transactions that had an announcement date of M&A between January 1st 1995 and November 16th 2016, were completed, had a disclosed M&A deal value over the $0.001million, and were based in either the United States or Republic of Korea were collected. The acquiring corporation and the target corporation were replaced by the SIC (Standard Industry Classification) code information on the transaction date (e.g. "Samsung Electronics → AST Research Inc" : "3663 → 3571"). The whole number of M&A transactions satisfying the above search conditions was 71,264. In order to observe the change of M&A trend over time, whole data were divided into Phase 1 (1995-2001), Phase 2 (2002-2008), and Phase 3 (2009-2016). The number of M&A transactions in each period was 27,978, 21,183, and 22,103 respectively. The reason why we separated the dataset in 2002 and 2009 is that we would investigate the change in M&A trend on the basis of ex-ante and ex-post analysis in global economic crisis. In 2002, there are lots of bankruptcies of IT corporation, generally called 'Dot com bubble'. The worst financial crisis since the great depression of the 1930s was happened in 2008 with a crisis in the subprime mortgage market in U.S. We wondered these economic crisis how affect M&A trend at the industry level.

4.2. Identification of patterns of M&A at the industry level

4.2.1 Extraction of significant M&A transaction rules

We extracted significant M&A transaction rules among all transactions to identify which transactions appeared frequently and which industries built a strong transaction relationship with others. In order to do this, we modified the association rule mining and redefined the five major measures which are $Support_{ac}(X)$, $Support_{ta}(Y)$ $Support_{ac\to ta}(X \to Y)$, $Confidence_{ac\to ta}(X \to Y)$, and $Lift_{ac\to ta}(X \to Y)$. We selected the significant M&A transactions by cut-off values of $Support_{ac\to ta}(X \to Y)$, $Confidence_{ac\to ta}(X \to Y)$. The cut off values of $Support_{ac\to ta}(X \to Y)$, $Confidence_{ac\to ta}(X \to Y)$ were 0.0001 and 0.1 respectively. Significant M&A transaction rules were extracted using the two values above and $Lift_{ac\to ta}(X \to Y)$ greater than 1. The value of $Lift_{ac\to ta}$ was 1 when an industry in antecedent and consequent of the transactions were independent and showed the values far from 1 when the transaction rules had a logical implication. 544, 472, 429 significant M&A transaction rules were extracted according to Table 1, Table 2, and Table 3.

Table 1. Significant M&A transaction rules in Phase 1 (1995-2001)

$Transaction\ rule_{ac\to ta}$ $(X \to Y)$	$Support_{ac}(X)$	$Support_{ta}(Y)$	$Support_{ac\to ta}$ $(X \to Y)$	$Confidence_{ac\to ta}$ $(X \to Y)$	$Lift_{ac\to ta}$ (X → Y)
6798→6512	0.0577	0.0383	0.0288	0.4985	13.0090
7372→7372	0.0469	0.0580	0.0251	0.5358	9.2311
1311→1311	0.0250	0.0275	0.0190	0.7600	27.6506
6021→6021	0.0419	0.0305	0.0183	0.4360	14.3008
4832→4832	0.0150	0.0172	0.0131	0.8759	51.0537
…	…	…	…	…	…
7521→7521	0.0003	0.0004	0.0003	1.0000	2331.5000
8351→8351	0.0002	0.0005	0.0002	1.0000	1998.4286
8244→8221	0.0002	0.0006	0.0002	1.0000	1748.6250
5198→5198	0.0001	0.0003	0.0001	1.0000	3996.8571
2361→2361	0.0001	0.0002	0.0001	1.0000	4663.0000
Mean	*0.0027*	*0.0068*	*0.0008*	*0.3704*	*554.9457*
Median	*0.0009*	*0.0015*	*0.0003*	*0.3090*	*200.3553*

In Phase 1 (1995-2001), a total of 544 M&A transaction rules were extracted. Among them, 343(63.05%) M&A transaction rules were composed of related industries and 201(36.95%) M&A transaction rules were made up of unrelated industries. M&A transaction rules with the highest $Support_{ac\to ta}(X \to Y)$ was 6798 (real estate investment trusts) → 6512 (operators of nonresidential buildings), and the top five M&A transaction rules for $Support_{ac\to ta}(X \to Y)$ were 7372 (prepackaged software) → 7372 (prepackaged software), 1311 (crude petroleum and natural gas) → 1311 (crude petroleum and natural gas), 6021 (national commercial bank) → 6021 (national commercial bank), 4832 (radio broadcasting station) → 4832 (radio broadcasting station). The five M&A transaction rules above are M&A transaction rules that appeared the most frequently in Phase 1. The higher the $Support_{ac\to ta}(X \to Y)$, the more active the transaction between the antecedent and consequence industries. Among the top five M&A transaction rules, four transaction rules were composed of unrelated industries. The number of M&A transaction rules with the $Confidence_{ac\to ta}(X \to Y)$ of 1 was 16, details of which follow. 8244 (business and secretarial schools) → 8221 (elementary and secondary school), 8351 (child day care services) → 8351(child day care services), 5995 (optical goods stores) → 5995 (optical goods stores), 6553 (cemetery subdividers and developers) → 6553 (cemetery subdividers and developers), 7521 (automobile parking) → 7521 (automobile parking), 2311 (men's and boys' suits, coats and overcoats) → 5136 (men's and boys' clothing and furnishing), 3535 (conveyors and conveying equipment) → 3535 (conveyors and conveying equipment), 2047 (dog and cat food) → 2047 (dog and cat food), 4222 (refrigerated warehousing and storage) → 4222 (refrigerated warehousing and storage), 5198 (paint, varnishes and supplies) → 5198 (paint, varnishes and supplies), 2361 (girls' children's and infants' dresses, blouses, and shirts) → 2361 (girls' children's and infants' dresses, blouses, and shirts), 7342 (disinfecting and pest control services) → 7342 (disinfecting and pest control services), 3951 (pen, mechanical pencils and parts) → 3951 (pen, mechanical pencils and parts), 3534 (elevator and moving stairways) → 3534 (elevator and moving stairways), 2448 (wood pallets and skids) → 2448 (wood pallets and skids), 2131 (chewing and smoking tobacco and snuff) → 2131 (chewing and smoking tobacco and snuff). M&A transaction rules with a $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$ of 1 mean that only the consequence industry was considered to be the target industry of M&A by the antecedent industry. In Phase 1, the $Support_{ac\rightarrow ta}(X \rightarrow Y)$ of the M&A transaction rules with a $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$ of 1 is lower than the average $Support_{ac\rightarrow ta}(X \rightarrow Y)$ of M&A transaction rules. 14 of the 16 M&A transaction rules are composed of related industries.

In the case of M&A transaction rules: 1311 (crude petroleum and natural gas) → 1311 (crude petroleum and natural gas), it can be regarded that the most important transaction rule of M&A has both high $Support_{ac\rightarrow ta}(X \rightarrow Y)$ and high $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$. In both the U.S and global markets, the M&A of the petroleum and natural gas industries rose sharply from the late 1990s to the early 2000s. This is due to the global economic boom that began in the mid to late 1990s, and petroleum companies that had undergone restructuring in the early 1990s were actively involved in the M&A market in late 1990s. Especially in 1998, the crude petroleum and natural gas industry had great M&A deals which of deal value approached $ 154 billion. The major transactions were the merger of BP and Amoco, and the merger of Exxon and Mobil.

Table 2. Significant M&A transaction rules in Phase 2 (2002-2008)

$Transaction\ rule_{ac\to ta}$ $(X \to Y)$	$Support_{ac}(X)$	$Support_{ta}(Y)$	$Support_{ac\to ta}$ $(X \to Y)$	$Confidence_{ac\to ta}$ $(X \to Y)$	$Lift_{ac\to ta}$ (X → Y)
7372→7372	0.0505	0.0694	0.0298	0.5907	8.5057
1311→1311	0.0342	0.0376	0.0283	0.8262	21.9869
6798→6512	0.0550	0.0308	0.0211	0.3842	12.4639
6021→6021	0.0356	0.0336	0.0207	0.5822	17.3465
3674→3674	0.0176	0.0190	0.0095	0.5416	28.5367
…	…	…	…	…	…
7372→7372	0.0505	0.0694	0.0298	0.5907	8.5057
7215→7215	0.0002	0.0002	0.0002	1.0000	4236.6000
8351→8351	0.0002	0.0003	0.0002	1.0000	3026.1429
1761→1761	0.0002	0.0002	0.0002	1.0000	4236.6000
2015→2015	0.0002	0.0003	0.0002	1.0000	3026.1429
Mean	*0.0027*	*0.0079*	*0.0009*	*0.3612*	*400.3032*
Median	*0.0012*	*0.0021*	*0.0003*	*0.3077*	*149.8022*

In Phase 2 (2002-2008), a total of 472 M&A transaction rules were extracted. Among them, 287(60.81%) M&A transaction rules were composed of related industries and 185(39.19%) M&A transaction rules were made up of unrelated industries. It can be seen that the proportion of unrelated M&A transaction rules has increased slightly compared to Phase 1. M&A transaction rules with the highest $Support_{ac\to ta}(X \to Y)$ was 7372 (prepackaged software) → 7372 (prepackaged software), and the top 5 support rules were 1311 (crude petroleum and natural gas) → 1311 (crude petroleum and natural gas), 6798 (real estate investment trusts) → 6512 (operators of nonresidential buildings), 6021 (national commercial banks) → 6021 (national commercial banks), 3674(semiconductors and related devices) → 3674 (semiconductors and related devices). The number of M&A transaction rules with a $Confidence_{ac\to ta}(X \to Y)$ of 1 was 9, details of which follow: 7342 (disinfecting and pest control services) → 7342 (disinfecting and pest control services), 7215 (coin-operated laundries and dry cleaning) → 7215 (coin-operated laundries and dry cleaning), 8351 (child day care services) → 8351(child day care services), 1761 (roofing, siding, and sheet metal work) → 1761 (roofing, siding, and sheet metal work), 2015 (poultry slaughtering and processing) → 2015 (poultry slaughtering and processing), 4491 (marine cargo handling) → 4491 (marine cargo handling), 5736 (musical instrument stores)→5736 (musical instrument stores), 7521 (automobile parking) → 7521 (automobile parking), 3715 (Truck Trailer) → 3715(Truck Trailer).

In Phase 2, transaction rule of M&A: 7372 (prepackaged software) → 7372 (prepackaged software) is the most frequently occurring transaction rule, and the $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$ is about 0.6. Since the dot-com bubble of the early 2000s, each country started to have started to invest in the IT industry as a new growth engine, in the software industry, a huge amount of investment was made by the U.S. government. A variety of innovative companies started to emerge centering in Silicon Valley. The reason for the frequent M&A transaction among software companies in Phase2 was to acquire new technology and diversify the business in a short period of time. Microsoft merged with Groove, IBM acquired Filenet and Micromuse Inc, and Oracle acquired about 20 other software companies including Peoplesoft. These M&A transactions brought tremendous funding to the software industry. HP paid $ 18.6 billion to acquire Compaq in 2002 and Symantec completed a M&A deal with Veritas paying $ 13.5 billion in 2005.

Table 3. Significant M&A transaction rules in Phase 3 (2009-2016)

$Transaction\ rule_{ac\rightarrow ta}$ $(X \rightarrow Y)$	$Support_{ac}(X)$	$Support_{ta}(Y)$	$Support_{ac\rightarrow ta}$ $(X \rightarrow Y)$	$Confidence_{ac\rightarrow ta}$ $(X \rightarrow Y)$	$Lift_{ac\rightarrow ta}$ (X → Y)
6798→6512	0.1004	0.0692	0.0442	0.4398	6.3541
1311→1311	0.0317	0.0402	0.0260	0.8188	20.3584
6021→6021	0.0242	0.0288	0.0182	0.7528	26.1214
7372→7372	0.0326	0.0537	0.0175	0.5361	9.9745
6798→7011	0.1004	0.0293	0.0146	0.1451	4.9497
...	...	...	...	...	...
6798→6513	0.1004	0.0178	0.0103	0.1027	5.7788
4226→4226	0.0002	0.0013	0.0002	1.0000	789.3929
3792→3792	0.0002	0.0005	0.0002	1.0000	2009.3636
4481→4481	0.0001	0.0002	0.0001	1.0000	5525.7500
3449→3449	0.0001	0.0003	0.0001	1.0000	3157.5714
Mean	*0.0029*	*0.0094*	*0.0009*	*0.3326*	*331.6994*
Median	*0.0011*	*0.0022*	*0.0003*	*0.2857*	*128.8054*

In Phase 3, a total of 429 M&A transaction rules were extracted. Among them, 261 (60.81%) M&A transaction rules were composed of related industries and 168 (39.19%) M&A transaction rules were made up of unrelated industries. The M&A transaction rules with the highest $Support_{ac\rightarrow ta}(X \rightarrow Y)$ was 6798 (real estate investment trusts) → 6512 (operators of nonresidential buildings), and the top 5 support rules were 1311 (crude petroleum and natural gas) → 1311 (crude petroleum and natural gas), 6021 (national commercial banks) → 6021 (national commercial banks), 7372 (prepackaged software) → 7372 (prepackaged software), 6798(real estate investment trusts) → 7011 (hotels and motels). The number of M&A transaction rules with a $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$ of 1 was 4 details of which following: 4226 (special warehousing and storage, not elsewhere classified) → 4226 (special warehousing and storage, not elsewhere classified), 3792 (travel trailers and campers) → 3792 (travel trailers and campers), 4481 (deep sea transportation of passengers, except by ferry) → 4481 (deep sea transportation of passengers, except by ferry), 3449 (miscellaneous structural metal work) → 3449 (miscellaneous structural metal work). In Phase 3, we examine the transaction rule of M&A 6798(real estate investment trusts) → 6512(operators of nonresidential buildings). Transaction rule 6798 (real estate investment trusts) → 6512 (operators of nonresidential buildings), which showed a high $Support_{ac \to ta}(X \to Y)$ even during Phase 1 and 2 showed an overwhelmingly high $Support_{ac \to ta}(X \to Y)$ in Phase 3.

In particular, M&A in the real estate investment trust industry grew nearly 60% in the US in 2015. This phenomenon resulted from the triple quantitative easing and low interest rate trends in the U.S. Federal Reserve system since 2008. Real estate investment trusts were able to raise capital at low interest rates in Phase 3 (2009-2016), but because of the quantitative easing, the price of land, which is often regarded as riskless asset, continued to rise due to abundant funds being released to the market. As a result, real estate investment trusts have recently tried to make profit through direct investment and have chosen direct M&A as a management strategy. As of 2015, real estate investment trusts totaled $ 25 billion.

4.2.2. Generation of M&A transaction relationship network

We constructed an M&A transaction relationship network to visualize the directed transaction relationships between industries and measure the characteristics of each industry within the M&A context based on network analysis. The resulting M&A transaction rules were the source of node and edge lists. Fig 5, Fig 6, and Fig 7 show the M&A transaction relationship network in each Phase. In the network, nodes and links represents industry and M&A transaction relationships between industries respectively. When constructing initial network, the value of links is $Confidence_{ac \to ta}(X \to Y)$ of given transaction rule. In order to measure characteristics of industry within M&A context, the value of links were changed twice : the frequency of the given transaction rule and the average deal value of the given transaction rule in the whole transaction. The size of the node and node label indicates degree-centrality and thickness of link shows the value of link.

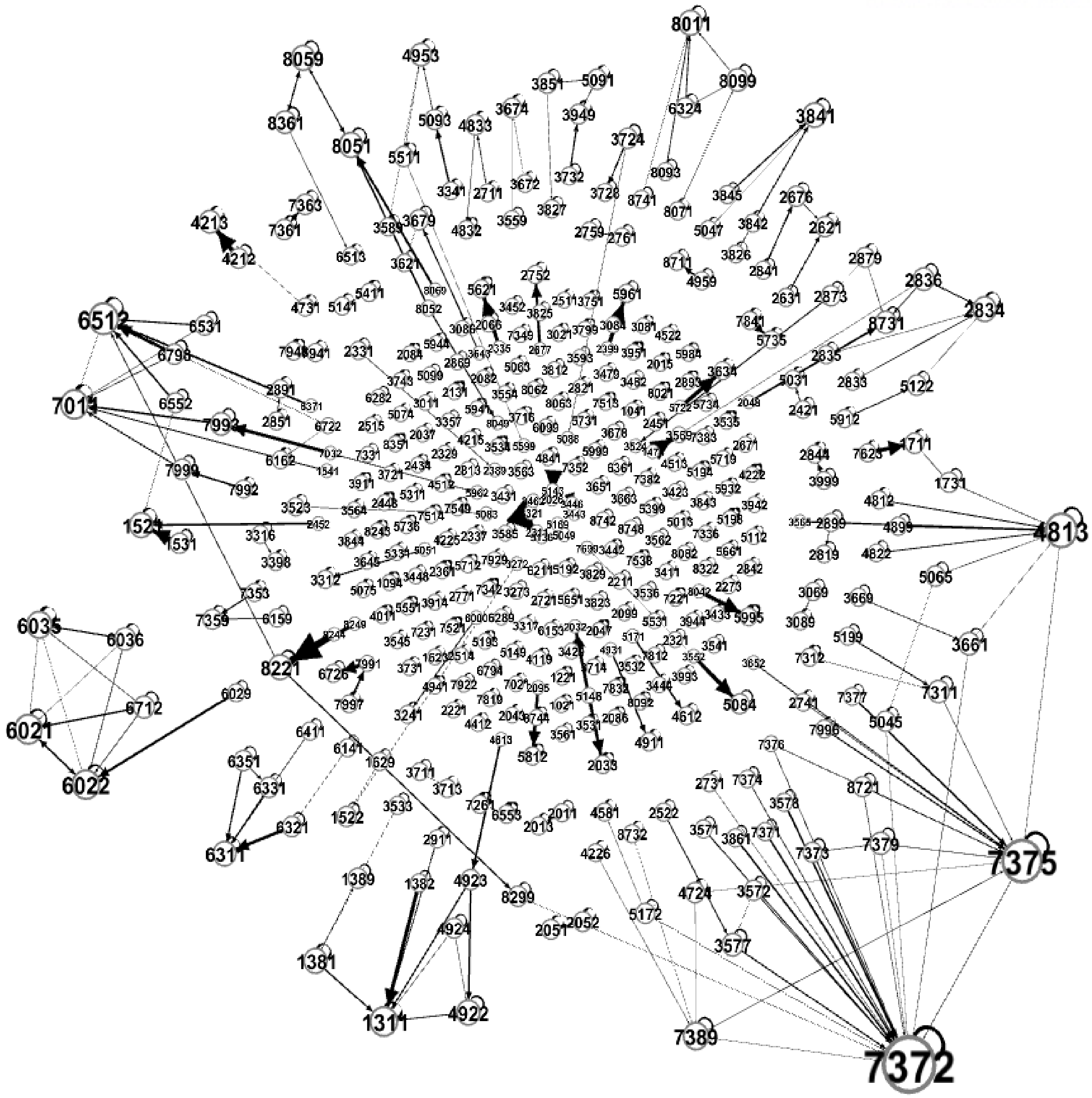

Figure 5. M&A transaction relationship network in Phase 1 (1995-2001)

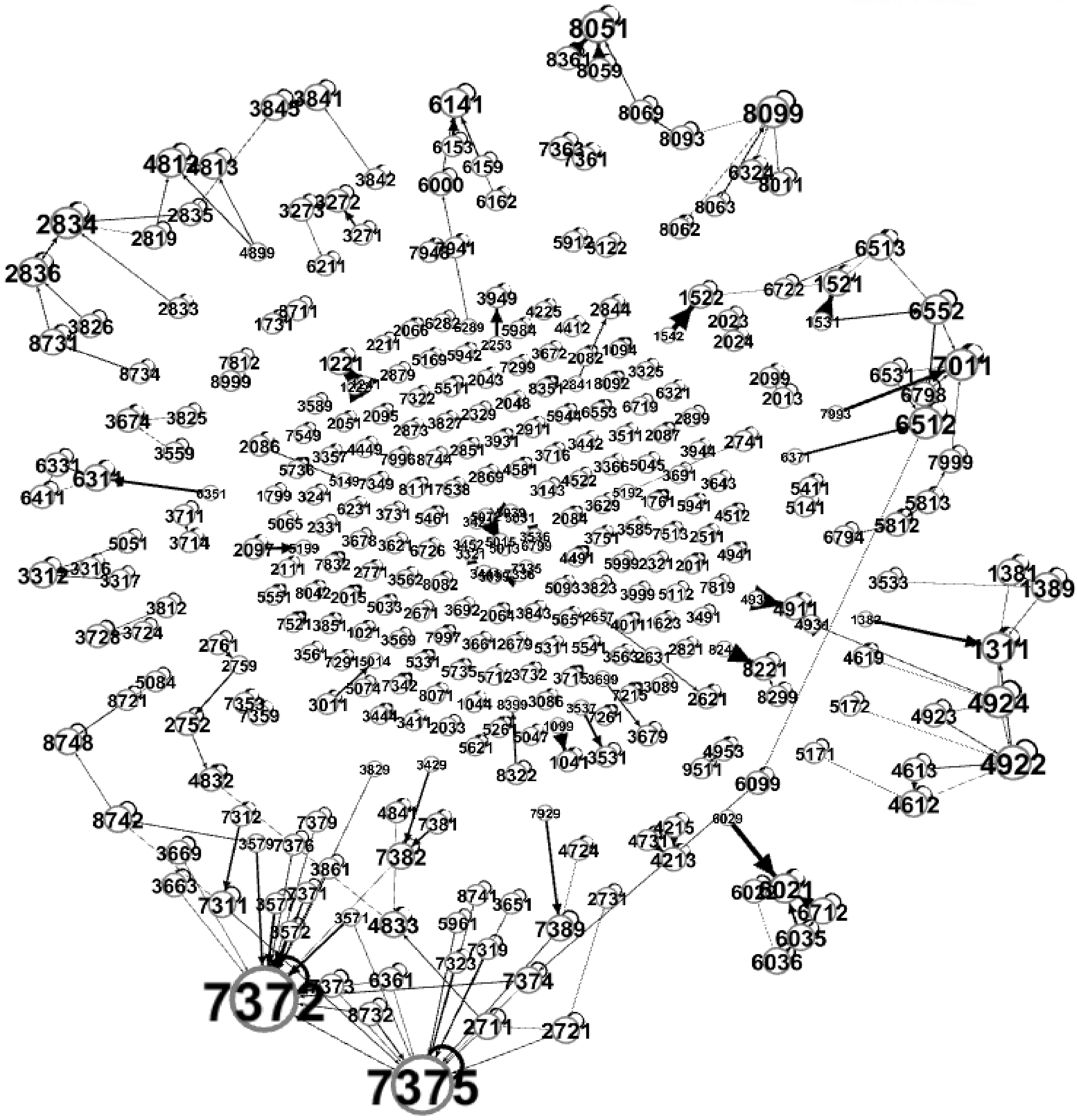

Figure 6. M&A transaction relationship network in Phase 2 (2002-2008)

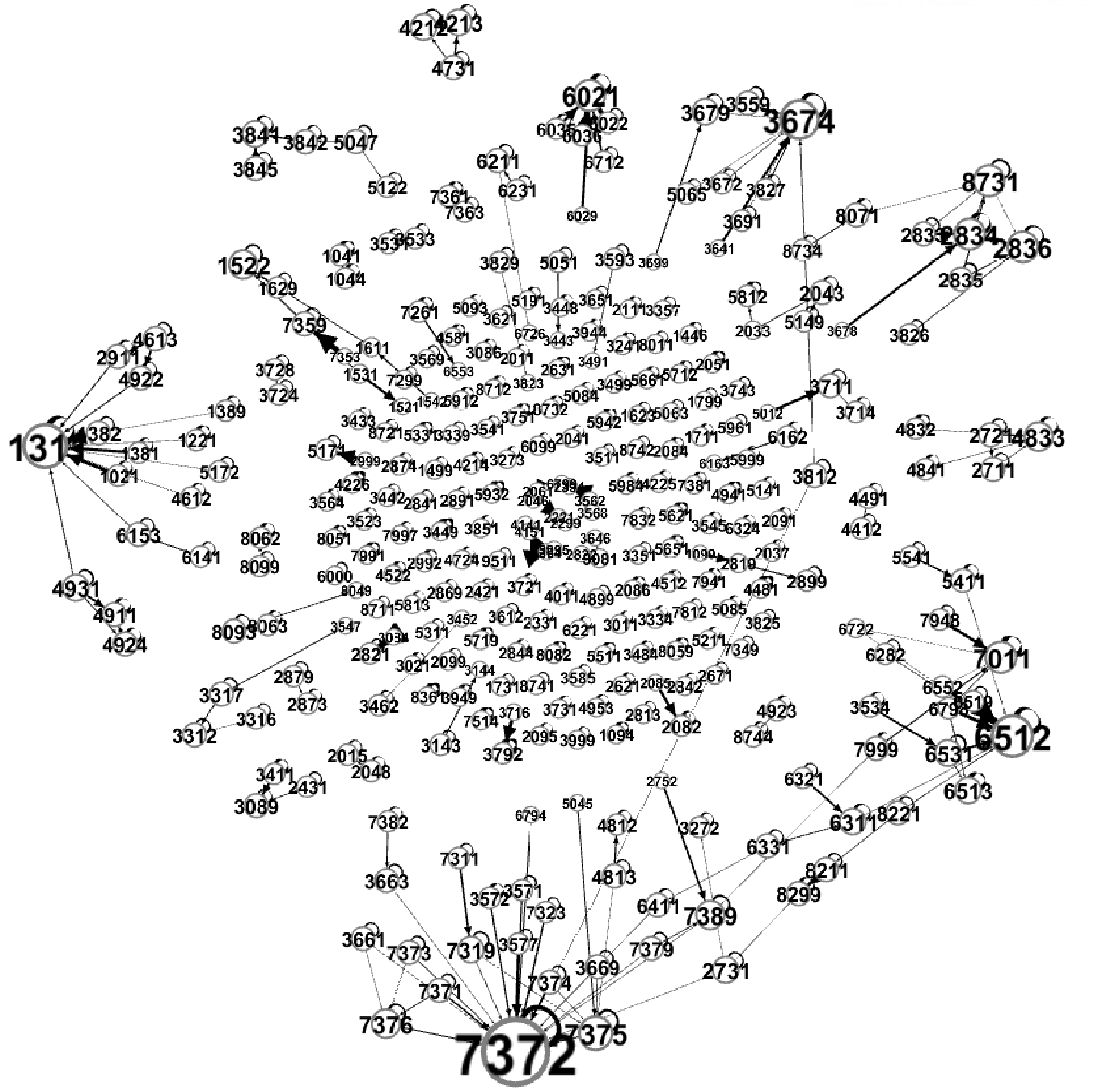

Figure 7. M&A transaction relationship network in Phase 3 (2009-2016)

Based on the concept of in-degree and out-degree centrality, the characteristics of each node are measured. Table 2 summarizes the characteristics of each industry and six indices (*The degree of acquirer, The degree of target, The degree of merge-diversity, The degree of merged-diversity, Average-invest deal value, Average-invested deal value*).

Table 4. Characteristics of industry within M&A context in Phase 1 (1995-2001)

Industry	*The degree of acquirer*	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*	*Average-invest deal value*	*Average-invested deal value*
6798	1615.0000	286.0000	3.0000	1.0000	102.0580	255.4796
7372	1312.0000	1624.0000	1.0000	19.0000	57.8697	82.7450
6512	55.0000	1072.0000	2.0000	7.0000	44.3374	58.8204
6021	1172.0000	853.0000	3.0000	5.0000	315.6916	372.5597
1311	700.0000	769.0000	1.0000	7.0000	225.4415	232.2317
…	…	…	…	…	…	…
7379	134.0000	204.0000	4.0000	1.0000	100.6258	5.3345
6036	96.0000	140.0000	4.0000	1.0000	270.1995	5.3193
7375	548.0000	803.0000	2.0000	12.0000	73.3835	61.0133
3721	12.0000	16.0000	1.0000	1.0000	1787.7167	1340.7875
2911	70.0000	49.0000	2.0000	1.0000	1121.2620	1438.6974
Mean	57.2370	63.6514	1.3802	1.3812	77.4938	64.3922
Median	18.0000	23.0000	1.0000	1.0000	29.9276	19.3573

In Phase 1 (1995-2001), 6798 (real estate investment trusts) had the highest *The degree of acquirer* value. This means that 6798 (real estate investment trusts) merged most actively with other industries, as the acquirer industry. 7372 (prepackaged software) had the highest $The\ degree\ of\ target$ value and $The\ degree\ of\ merged - diversity$. A total number of industries that considered the 7372 (prepackaged software) as target industry was 16. 6512 (operators of nonresidential buildings) had the second highest $The\ degree\ of\ target$ value and a total number of industries that merged with 6512 (operators of nonresidential buildings) was 7. In terms of 1311 (crude petroleum and natural gas), it belonged to top industry in both characteristics that were *The degree of acquirer* and *The degree of target*. High *The degree of acquirer* and high *The degree of target* of 1311 explained that M&A transactions that 1311 (crude petroleum and natural gas) merged with other industries and M&A transactions that other industries merged with 1311 (crude petroleum and natural gas) were actively committed. 7379 (computer related services, not elsewhere classified) and 6036 (savings institutions, not federally chartered) were top two industries that they merge with diverse industries. In addition, we confirmed that 3721 (aircraft) is the representative with regard to *Average-invest deal value*, *Average-invested deal value*. 3721 (aircraft) only merged with related industries among transaction rules since *The degree of merge-diversity* and *Average-invested deal value* are both 1. It means that big deals were took place within the 3721 (aircraft) industry. 3721 (aircraft) invested an average of $ 1,787.7167 billion for M&A transactions to merge with other merger transactions, and an average of $ 1,340.7875 billion flowed into 3721 (aircraft) from acquirer industries for deal value. 2911 (petroleum refining industry) was set to the highest *Average-invested deal value* in the M&A market during Phase 1, and acquirer industries paid an average of $ 1438.6974 million to complete the merger with the 2911(petroleum refining industry).

Table 5. Characteristics of industry within M&A context in Phase 2 (2002-2008)

Industry	*The degree of acquirer*	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*	*Average-invest deal value*	*Average-invested deal value*
6798	1166.0000	186.0000	3.0000	1.0000	218.5348	497.9636
7372	1070.0000	1471.0000	1.0000	18.0000	159.3852	144.9244
1311	725.0000	796.0000	1.0000	6.0000	295.3207	286.4442
6021	754.0000	711.0000	1.0000	5.0000	376.1289	443.6941
6552	139.0000	96.0000	4.0000	2.0000	117.9157	16.2436
…	…	…	…	…	…	…
7375	413.0000	618.0000	2.0000	15.0000	56.0219	54.8017
1021	8.0000	10.0000	1.0000	1.0000	3339.8953	2671.9162
2911	50.0000	54.0000	1.0000	1.0000	3066.5160	2839.3667
2111	14.0000	10.0000	1.0000	1.0000	1789.6831	2505.5563
5331	7.0000	8.0000	1.0000	1.0000	2235.8857	1956.4000
Mean	48.7387	55.6486	1.4174	1.4174	130.7767	105.4867
Median	17.0000	20.0000	1.0000	1.0000	48.9918	25.3114

In Phase 2 (2002-2008), 6798 (real estate investment trusts) had the highest *The degree of acquirer* as in Phase 1. 7372 (prepackaged software) had the highest *The degree of target* and *The degree of merged-diversity*. The total number of industries that considered the 7372 (prepackaged software) as a target industry was 18. 1311 (crude petroleum and natural gas) and 6021 (national commercial bank) were typical industries that had both high *The degree of acquirer* and high *The degree of target*. 6552 (land subdividers and developers, except cemeteries) was the industry that merged with the most diverse industries. 7375(information retrieval services) had the second highest *The degree of merged-diversity*. 1021 (copper ores), 2911 (petroleum refining industry), 2111 (cigarettes) and 5331(variety stores) are the industries which had both high *Average-invest deal value* and high *Average-invested* deal value*. Considering the four other indices, we were able to analogize that four industries merged with an identical industry respectively via the small number of big deals.

Table 6. Characteristics of industry within M&A context in Phase 3 (2009-2016)

Industry	*The degree of acquirer*	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*	*Average-invest deal value*	*Average-invested deal value*
6798	2219.0000	0.0000	3.0000	0.0000	85.0959	0.0000
7372	720.0000	1188.0000	1.0000	20.0000	189.0336	181.7146
1311	701.0000	889.0000	1.0000	11.0000	288.5891	380.9365
6512	82.0000	1530.0000	1.0000	10.0000	49.0353	100.2029
2731	28.0000	31.0000	4.0000	1.0000	37.1990	21.7876
…	…	…	…	…	…	…
3674	331.0000	522.0000	1.0000	9.0000	381.6031	253.7690
7375	252.0000	444.0000	2.0000	6.0000	152.2254	50.6686
5331	8.0000	11.0000	1.0000	1.0000	4155.6151	3022.2655
2111	19.0000	13.0000	1.0000	1.0000	2198.7586	3213.5703
5211	7.0000	8.0000	1.0000	1.0000	2461.0286	2153.4000
Mean	49.4239	61.3010	1.3883	1.3883	189.7527	153.4614
Median	19.0000	24.0000	1.0000	1.0000	57.1306	33.1726

In Phase 3 (2002-2008), 6798 (real estate investment trusts) had the highest *The degree of acquirer* and appeared only as the acquirer industry within significant transaction rules. 6512 (operators of nonresidential buildings) had the highest *The degree of target*. 7372 (prepackaged software) had the highest *The degree of merged-diversity* and the total number of industries that considered the 7372 (prepackaged software) as a target industry was 20. 2731 (books: publishing or publishing and printing) did not actively take other industries over but succeeded in merging with the most diverse industries. In terms of 3674 (semiconductor and related devices), It was regarded as the target industry of a total of nine industries and sold for an average of $ 253.7690 million. 7375 (information retrieval services) received attention in M&A from a total of six industries, but we confirmed that the average deal value was made at a relatively low value of $ 50.6686 million. 5331(variety stores) had the highest *Average-invest deal value* and considering other indices, the small number of big deals occurred within industry as Phase 2. 2111 (cigarettes) had the highest *Average-invested deal value* and the 5211 (lumber and other building materials dealers) had high value both in *Average-invest deal* *value* and *Average-invested deal value*.

4.2.3. Identification of Dynamic & Structural patterns of M&A

In this section, we identify M&A patterns based on the results generated in Section 4.2.1. M&A patterns are interpreted from two perspectives: dynamic patterns of M&A and structural patterns of M&A. First, in terms of dynamic patterns of M&A, we compared the two indicators ($\mathrm{Support}_{ac\rightarrow \mathrm{ta}}(X \rightarrow Y)$, $\mathrm{Confidence}_{ac\rightarrow ta}(X \rightarrow Y)$) measured in Section 4.2.1 between Phase 1 and Phase 2, Phase 2 and Phase 3 to identify the change of M&A relationship trend. Second, in terms of structural patterns, we grouped significant M&A transaction rules with similar characteristics into several clusters based on the indicators measured in Section 4.2.1. and 4.2.2. via the K-means cluster algorithm.

4.2.3.1. Dynamic patterns of M&A

Two indicators - $\mathrm{Support}_{ac\rightarrow \mathrm{ta}}(X \rightarrow Y)$ and $\mathrm{Confidence}_{ac\rightarrow ta}(X \rightarrow Y)$ calculated in Section 4.2.1.- were employed to identify the dynamic patterns of M&A. For this, the change of $\mathrm{Support}_{ac\rightarrow \mathrm{ta}}(X \rightarrow Y)$ and $\mathrm{Confidence}_{ac\rightarrow ta}(X \rightarrow Y)$ of 296, 254 M&A transaction rules existing between Phase 1 and 2 and between Phase 2 and 3 were calculated respectively. The results are shown in Table 7 and Table 8. The results are normalized and a dynamic pattern of M&A map is constructed as shown in Fig. 8 and Fig. 9. This map presents a tool that identifies how the M&A transaction rules among the entire industry or industry that users are interested changed in over time. The dynamic patterns of M&A map used is based on changes in frequency of the M&A transaction rules and changes in connectivity of the M&A transaction rules. The M&A transaction rules for each area can be interpreted as the following patterns.

The first quadrant (Emerging & Strongly-connected area): The patterns of M&A that belong to the first quadrant area have an increasing appearance rate over time, and the connectivity between the antecedent industry and the consequence industry is strongly connected. These patterns are likely to be the major industries in the next period, with a large number of companies belonging to the antecedent industry intensively taking over the companies belonging to the consequence industry to achieve and sustain competitive advantages.

The second quadrant (Fading & Strongly-connected area): The patterns of M&A that belong to the second quadrant area have a low appearance rate over time, but the connectivity between the antecedent industry and the consequence industry is strongly connected. These patterns have declined from the peak M&A attention in the market, and it is possible that a small number of companies belonging to the antecedent industry will concentrate on the companies belonging to the consequence industry to consolidate the market situation.

The third quadrant (Fading & Weakly-connected area): The patterns of M&A belonging to the third quadrant area have a low appearance rate over time, and the connectivity between the antecedent industry and the consequence industry is loosened. These patterns may be due to the cases where companies affiliated with the antecedent industry have withdrawn from the companies of the consequence industry due to failure of realization of their business purpose, and have been involved in M&A into other industries.

The fourth quadrant (Emerging & Weakly-connected area): The patterns of M&A belonging to the fourth quadrant area have a high appearance ratio over time, but the linkage between the antecedent industry and the consequence industry is loosened. These patterns may be due to the case that companies belonging to antecedent industry are more actively engaged in M&A with companies belonging to various other industries compared to companies belonging to consequence industry. It is a pattern that can be seen when the market confirms that the consequence industry is a promising industry but uncertainty is high.

Table 7. Change in $Support_{ac \to ta}(X \to Y)$ and $Confidence_{ac \to ta}(X \to Y)$ of each M&A transaction rules between Phase 1 and 2

M&A transaction rules	Change in $Support_{ac \to ta}(X \to Y)$	Change in $Confidence_{ac \to ta}(X \to Y)$
1311→1311	0.0093	0.0662
7372→7372	0.0047	0.0548
6035→6035	-0.0101	-0.3121
6798→6512	-0.0076	-0.1142
…	…	…
2011→2011	0.0002	0.6000
5331→5331	0.0000	0.4481
2033→2033	-0.0001	-0.5635
7538→7538	0.0000	-0.3750

Table 8. Change in $Support_{ac \to ta}(X \to Y)$ and $Confidence_{ac \to ta}(X \to Y)$ of each M&A transaction rules between Phase 2 and 3

M&A transaction rules	Change in $Support_{ac \to ta}(X \to Y)$	Change in $Confidence_{ac \to ta}(X \to Y)$
6798→6512	0.0230	0.0556
6798→7011	0.0053	-0.0238
7372→7372	-0.0124	-0.0545
4832→4832	-0.0071	-0.1773
…	…	…
8361→8361	0.0008	0.5494
3572→3572	0.0005	0.4039
2015→2015	-0.0001	-0.7000
4491→4491 0.0000	-0.6364	

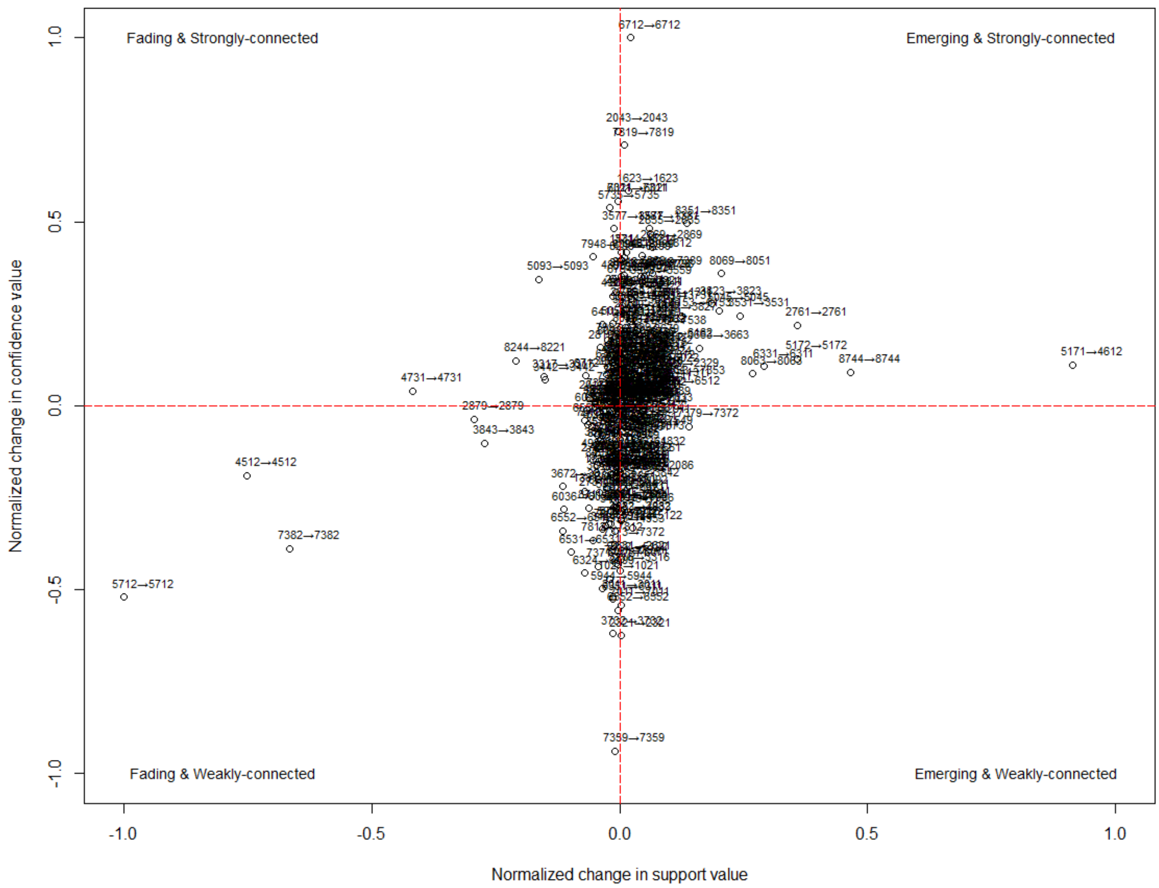

Figure 8. Dynamic patterns of M&A map between Phase 1 and 2

In between Phase 1 and 2, the typical M&A transaction rules classified as Emerging & Strongly-connected pattern are as follows. 5171 (oil bulk station and terminal industry) → 4612 (crude oil pipeline industry), 8744 (facility support management service industry) → 8744 (facility support management service), 2761 (various office print industry) → 2761 (various office print industry) and the representative acquirer corporation and the target corporation by transaction each rule are 5171(Crude oil pipeline industry) →4612 (crude oil pipeline industry): Tesoro Alaska Petroleum Co → Kenai Pipe Line, 8744 (crude oil pipeline industry) → 8744 (crude oil pipeline industry): Corrections Corp. of America → Eden Detention Center, 2761 (various office printing industry) → 2761 (various office printing industry): Ennis Business Forms Inc → Northstar Computer Forms Inc.

4731 (cargo and freight transport industry) → 4731 (freight and freight transport industry), 5093 (scrapped waste and waste disposal industry) → 5093 (scrapped and waste disposal industry), 8244 (business and secretarial education industry) → 8221 (university and professional education industry) are the representatives classified as Fading & Strongly-connected pattern. The representative acquirer corporation and the target corporation by each transaction rule are 4731 (freight and cargo transportation industry) → 4731 (freight and cargo transportation industry): Geo Logistics Corp → Goldman Industries Inc, 5093 (scrapped waste and waste disposal industry) → 5093 (scrapped and waste disposal industry): Metal Management Inc → Goldin Industries Inc, 8244 (business and secretarial education industry) → 8221 (business and secretarial education industry): Corinthian Colleges Inc → Georgia Medical Institute.

The typical M&A transaction rules classified as Fading & Weakly-connected pattern are 5712 (furniture) → 5712 (furniture), 4512 (air transportation planning) → 4512 (air transportation planning), 7312 (security service system industry) → 7382 (security service system industry) and representative acquirer corporation and target corporation by each rule are 5712 (furniture industry) → 5712 (furniture industry): Heilig-Meyers Co → Rhodes Inc, 4512 (air transportation planning) → 4512 (air transport planning): American Airlines Inc → Trans World Airlines Inc, 7382 (Security Service System Industry) → 7382 (Security Service System Industry): Alarmguard Holdings Inc → Sentry Protective Systems.

Finally, the typical M&A transaction rules classified as Fading & Weakly-connected pattern are 6712 (bank holding company) → 6712 (bank holding company), 2043 (grain bread industry), 2043 (grain bread industry), 7819 (services allied to motion picture production) → 7819 (services allied to motion picture production). The representative acquirer corporation and the target corporation by each transaction rule are 6712 (bank holding company) → 6712 (bank holding company): Banc Kentucky Inc → Murray Banc Holding Co, 2043 (cereal breakfast) → 2043 (cereal breakfast): Ralcorp Holdings → Inc Post Cereal, 7819 (Film Production Related Service Industry) → 7819 (Film Production Related Service Industry): Four Media Co → Visualize Inc.

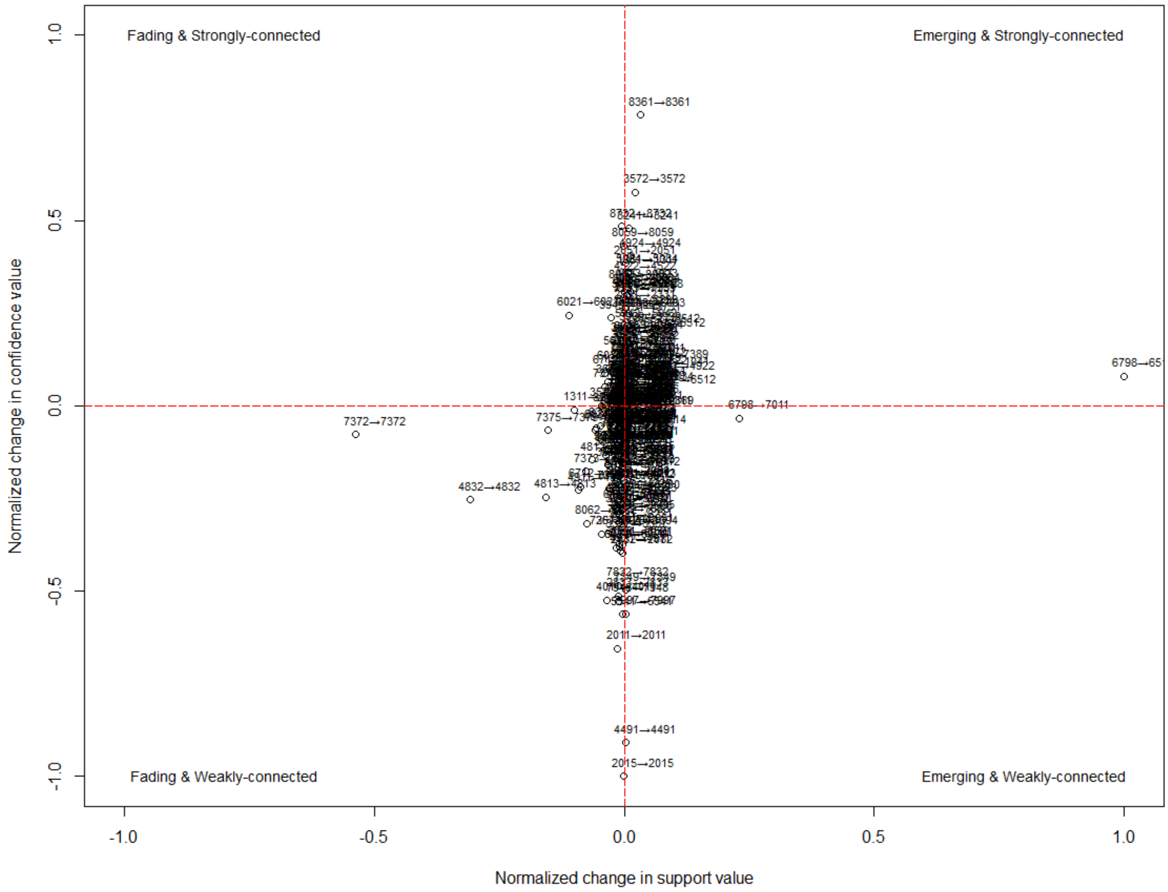

Figure 9. Dynamic patterns of M&A map between Phase 2 and 3

In between Phase 2 and 3, the typical M&A transaction rules classified as Emerging & Strongly-connected pattern are as follows. 6798 (real estate investment trust industry) → 6512 (non-residential building operation industry), 4922 (natural gas transportation industry) → 4922 (natural gas transportation industry), 7389 (business services, not elsewhere classified) → 7389 (business services, not elsewhere classified). The representative acquirer corporation and the target corporation by each transaction rule are 6798 (real estate investment trust industry) → 6512 (non-residential building operation industry): General Growth Properties Inc → First Colony Mall, Sugar Land, 4922 (natural gas transportation industry) → 4922 (natural gas transportation industry): Energy Transfer Partners LP → PennTex Midstream Partners LP, 7389 (business services, not elsewhere classified) → 7389 (business services, not elsewhere classified): eBay Inc → Internet Auction Co Ltd.

The typical M&A transaction rules classified as Fading & Strongly-connected pattern are 6021 (national commercial banking industry) → 6021 (national commercial banking industry), 6712 (bank holding company) → 6712 (bank holding company), 7375 (information search service industry) → 7372 (prepackaged software). The representative acquirer corporation and the target corporation by each transaction rule are 6021 (national commercial banking industry) → 6021 (national commercial banking industry): MB Financial Inc → American Chartered Bancorp Inc, 6712 (bank holding company) → 6712 (bank holding company): Yorktown Financial Holdings → CNBO Bancorp Inc, 7375 (information search service industry) → 7372 (prepackaged software): Facebook Inc → Instagram Inc.

The typical M&A transaction rules classified as Fading & Weakly-connected pattern are 7372 (software industry) → 7372 (software industry), 4832 (wireless communication broadcasting industry) → 4832 (wireless communication broadcasting industry), 4911 (power supply service industry) → 4911 (power supply service industry). The representative acquirer corporation and the target corporation by each transaction rule are 7372 (software industry) → 7372 (software industry): Samsung SDS Co Ltd → Miracom Inc, 4832 (wireless communication broadcasting industry) → 4832 (wireless communication broadcasting industry): Archway Broadcasting Group LLC → New East Commun-Radio Stn (2), 4911 (power supply service industry) → 4911 (power supply service industry): Korea East-West Power Co Ltd → Dongbu Power Dangjin Corp.

Finally, the typical M&A transaction rules classified as Fading & Weakly-connected pattern are 6798 (Real estate investment trust industry) → 7011 (Hotel and motel industry), 2869 (Uncategorized industrial organic chemical industry) → 2869 (Uncategorized industrial organic chemical industry), 4922 (Natural gas transportation industry) → 1311 Crude oil and natural gas industries). The representative acquirer corporation and the target corporation by each transaction rule are 6798 (Real estate investment trust industry) → 7011 (Hotel and motel industry): Hersha Hospitality Trust → Holiday Inn Express Hotel, 2869 (Uncategorized industrial organic chemical industry) → 2869 (Uncategorized industrial organic chemical industry): GlyEco Inc → Evergreen Recycling Co Inc, 4922 (Natural gas transportation industry) → 1311 Crude oil and natural gas industries): Western Gas Partners LP → Mountain Gas Resources LLC.

4.2.3.2. Structural patterns of M&A

We identified the structural patterns of M&A by conducting a cluster analysis for each Phase by using the $Support_{ac \to ta}(X \to Y)$, $Confidence_{ac \to ta}(X \to Y)$ value of the M&A transaction rules measured in section 4.2.1 and characteristics of industry calculated in section 4.2.2 as input values. In order to achieve this, this study employed a K-means cluster algorithm and set the optimal value of K based on WCSS (Within-Cluster Sum of Squares). WCSS were calculated according to the following formulation.

$$WCSS = \sum_{k=1}^{K} \sum_{i \in S_k} \sum_{j=1}^{p} (x_{ij} - \overline{x_{kJ}})^2$$

Where S_k represents kth set of clusters, $p$is the number of input and $\overline{x_{kJ}}$ is the jth objective of the kth cluster. The results of the cluster analysis by employing eleven input variables is organized according to Table 4. If the variables in given cluster is higher than the average of the variables in whole dataset, given cluster is characterized as the variables in given cluster which are higher than each average of the variables in whole dataset. This is because it is difficult to establish a criterion for measuring the degree of characteristics of each cluster. If the variables in given cluster are high or low comparing to the average of variables in whole dataset, it can be considered to reflect the characteristics of each cluster.

Table 10. Structural patterns of M&A in Phase 1 (1995-2001)

Cluster	Characteristics of pattern											Size of cluster
	Antecedent				*Consequence*				$Support_{ac\to ta}$ $(X \to Y)$	$Confidence_{ac\to ta}$ $(X \to Y)$	*Mean of deal value*	
	The degree of acquirer	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*	*The degree of acquirer*	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*				
1	69.6757	67.4595	501.7838	750.1892	2.4865	1.2432	1.8649	7.9459	0.0005	0.2150	154.1829	37
2	115.7333	114.2667	174.4000	209.6667	1.8667	2.0667	1.4667	3.1333	0.0014	0.2991	1159.2006	15
3	1381.8571	720.1429	786.8571	831.1429	2.7143	5.2857	2.1429	7.0000	0.0147	0.3000	237.6239	7
4	141.2222	166.4444	1312.0000	1624.0000	2.3889	2.0556	1.0000	19.0000	0.0009	0.1800	88.2371	18
5	423.8462	696.8462	561.6154	749.3846	2.0769	6.0769	1.9231	7.0000	0.0065	0.4159	127.1084	13
6	114.9245	128.3962	192.0377	215.0755	2.0566	1.7358	1.6981	3.1132	0.0011	0.2500	96.7068	53
7	67.0357	63.2857	80.5179	80.8750	1.7321	1.2143	1.4643	1.8214	0.0008	0.3427	447.3342	56
8	46.0000	41.5000	52.7500	56.5000	2.2500	1.5000	1.5000	1.5000	0.0004	0.2804	2728.5347	4
9	24.5161	29.0205	28.4721	35.9443	1.5367	1.1994	1.4018	1.4428	0.0003	0.4244	62.0062	341
mean	74.3162	76.6857	151.1287	191.3695	1.7426	1.4798	1.4798	2.9191	0.0008	0.3704	165.8663	
median	26.0000	30.5000	32.0000	41.5000	2.0000	1.0000	1.0000	2.0000	0.0003	0.3090	57.9621	

Cluster 1 consists of 37 M&A transaction rules highlighting low $Support_{ac\rightarrow ta}(X \rightarrow Y)$, low $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$. The antecedent's characteristics of M&A transaction rules are high *The degree of merge-diversity* and the consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target*, high *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 1 are 4812 (radiotelephone communications) → 4813 (telephone communications, except radiotelephone). 2911 (petroleum refining) → 1311 (crude petroleum and natural gas), 7379 (computer related services, not elsewhere classified) → 7375 (information retrieval services).

Cluster 2 consisted of 15 M&A transaction rules highlighting high $Support_{ac\rightarrow ta}(X \rightarrow Y)$ and high *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target.* Typical M&A transaction rules belonging to cluster 2 are 2834 (pharmaceutical preparations) → 2834 (pharmaceutical preparations), 3812 (search, detection, navigation, guidance, aeronautical and nautical systems and instruments) → 3812 (search, detection, navigation, guidance, aeronautical and nautical systems and instruments), 4911 (electric services) → 4911 (electric services).

Cluster 3 is composed of seven M&A transaction rules that are above average in all indices excluding $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$. The antecedent's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target* and high *The degree of merged-diversity*. The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target* and high *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 3 are 6021 (national commercial banks) → 6022 (state commercial banks), 6798 (real estate investment trusts) → 6798 (real estate investment trusts), 6798 (real estate investment trusts) → 7011 (hotels and motels).

Cluster 4 are composed of 18 M&A transaction rules highlighting low $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$ and low *Mean of deal value*. The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target,* and high *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 4 are 7379 (computer related service, not elsewhere classified) → 7372 (prepackaged software), 3572 (computer storage devices) → 7372 (prepackaged software), 5172 (petroleum and petroleum products wholesalers, except bulk stations and terminals) → 7372 (prepackaged software).

Cluster 5 consists of 13 M&A transaction rules highlighting high $Support_{ac\rightarrow ta}(X \rightarrow Y)$, high $Confidence_{ac\rightarrow ta}(X \rightarrow Y)$. *The degree of acquirer, The degree of target,* and *The degree of merged-diversity* of antecedent and *The degree of acquirer, The degree of target*, and *The degree of merged-diversity* of consequence are very high compared to average value. Typical M&A transaction rules are 1311 (crude petroleum and natural gas) → 1311 (crude petroleum and natural gas), 7011 (hotels and motels) → 7011 (hotels and motels), 6022 (state commercial banks) → 6035 (savings institutions, federally chartered).

Cluster 6 consists of 53 M&A transaction rules highlighting high $Support_{ac\to ta}(X \to Y)$, low *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are that *The degree of acquirer* and *The degree of target* are slightly above average value. The consequence's characteristics of M&A transaction rules are the same as antecedent's characteristics of M&A transaction rules. Typical M&A transaction rules are 5812 (eating places) → 5812 (eating places), 2836 (biological products, except diagnostic substances) → 2836 (biological products, except diagnostic substances), 3559 (special industrial machinery, not elsewhere) → 3674 (semiconductors and related devices).

Cluster 7 consists of 57 M&A transaction rules. The consequence's characteristics of M&A transaction rules are low *The degree of acquirer,* low *The degree of target*, and low *The degree of merged-diversity*. Typical M&A transaction rules are 2711 (newspapers: publishing, publishing and printing) → 2711 (newspapers: publishing, publishing and printing), 1521 (general contractors-sing-family-houses) → 1531 (general contractors-sing-family-houses), 4512 (air transportation, scheduled) → 4512 (air transportation, scheduled).

Cluster 8 consists of 4 M&A transaction rules highlighting low $Support_{ac\to ta}(X \to Y)$, low $Confidence_{ac\to ta}(X \to Y)$, and very high $Average\ deal\ value$. The consequence's characteristics of M&A transaction rules are low *The degree of acquirer,* low *The degree of target*, low *The degree of merge-diversity,* low *The degree of merged-diversity.* Typical M&A transaction rules are 4922 (natural gas transmission) → 4923 (natural gas transmission and distribution), 3721 (aircraft) → 3721 (aircraft), 6321 (accident and health insurance) → 6141 (personal credit institutions).

Finally, cluster 9 are composed of 341 M&A transaction rules highlighting low $Support_{ac\to ta}(X \to Y)$, the lowest *Mean of deal value* between clusters. They show the feature that has the value below the average in the whole indices excluding $Confidence_{ac\to ta}(X \to Y)$. Typical M&A transaction rules are 2511 (wood household furniture, except upholstered) → 2511 (wood household furniture, except upholstered), 8059 (nursing and personal care facilities, not elsewhere classified) → 8059 (nursing and personal care facilities, not elsewhere classified), 6553 (cemetery subdividers and developers) → 6553 (cemetery subdividers and developers).

Table 11. Structural patterns of M&A in Phase 2 (2002-2008)

Cluster	Characteristics of pattern											Size of cluster
	Antecedent				*Consequence*				$Support_{ac \to ta}$ $(X \to Y)$	$Confidence_{ac \to ta}$ $(X \to Y)$	*Mean of deal value*	
	The degree of acquirer	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*	*The degree of acquirer*	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*				
1	108.0435	139.6087	170.3261	310.5217	2.0435	2.0870	1.5217	3.8478	0.0016	0.2976	129.6415	46
2	85.5833	97.8750	534.8333	670.5833	2.4583	2.2500	1.6250	11.4583	0.0011	0.2360	154.9957	24
3	54.0000	60.0000	61.5000	71.8333	1.3333	1.1667	1.5000	1.8333	0.0004	0.4101	2614.2404	6
4	29.0000	32.0000	29.0000	32.0000	1.0000	1.0000	1.0000	1.0000	0.0007	0.5625	5738.4322	2
5	64.4091	67.5909	74.7727	84.9545	1.8182	1.4545	1.8182	1.9091	0.0014	0.4282	997.1987	22
6	1007.8333	589.3333	649.3333	716.8333	2.0000	5.3333	1.3333	7.0000	0.0191	0.4422	422.3349	6
7	50.7857	55.2286	62.5857	73.8000	1.6571	1.6286	1.5429	2.2000	0.0008	0.3876	361.5519	70
8	25.8029	28.9319	34.6237	44.1111	1.7240	1.2079	1.4803	1.6595	0.0004	0.3738	70.0590	279
9	98.5882	107.7647	1070.0000	1471.0000	2.2353	1.8824	1.0000	18.0000	0.0010	0.2186	120.3037	17
mean	57.8390	59.2966	124.7246	168.4809	1.8008	1.4958	1.4958	3.1186	0.0009	0.3605	229.2762	
median	25.5000	29.0000	34.0000	44.0000	2.0000	1.0000	1.0000	2.0000	0.0003	0.3077	92.6630	

Cluster 1 consists of 46 M&A transaction rules highlighting low $Average\ deal\ value$. The antecedent's characteristics of M&A transaction rules are high $Support_{ac \to ta}(X \to Y)$, high $Confidence_{ac \to ta}(X \to Y)$, and high *The degree of merged-diversity.* The consequence's characteristics of M&A transaction rules are high $Support_{ac \to ta}(X \to Y)$ and high $Confidence_{ac \to ta}(X \to Y)$. Typical M&A transaction rules belonging to cluster 1 are 2836 (biological products, except diagnostic substances) → 2834 (pharmaceutical preparations), 3825 (instruments for measuring and testing of electricity and electrical signals) → 3674 (semiconductors and related devices), 7999 (amusement and recreation services, not elsewhere classified) → 7011 (hotels and motels).

Cluster 2 consists of 24 M&A transaction rules highlighting low $Confidence_{ac \to ta}(X \to Y)$, low *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are high *The degree of merge-diversity,* high *The degree of merged-diversity*. The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target*, and high *The degree of merged-diversity*. Typical transaction rules belonging to cluster 2 of M&A are 7373 (computer integrated system design) → 7375 (information retrieval services), 4922 (natural gas transmission) → 1311 (crude petroleum and natural gas), 6035 (savings institutions, federally chartered) → 6021 (national commercial Banks).

Cluster 3 consists of 6 M&A transaction rules highlighting low $Support_{ac \to ta}(X \to Y)$ and high *Mean of deal value*. The consequence's characteristics of M&A transaction rules are low $Support_{ac \to ta}(X \to Y)$, low $Confidence_{ac \to ta}(X \to Y)$. Typical M&A transaction rules belonging to cluster 3 are 6231 (security and commodity exchanges) → 6231 (security and commodity exchanges), 2111 (cigarettes) → 2111 (cigarettes), 3711 (motor vehicles and passenger car bodies) → 3711 (motor vehicles and passenger car bodies).

Cluster 4 are composed of only two M&A transaction rules highlighting high $Confidence_{ac \to ta}(X \to Y)$, extremely high *Mean of deal value*. All indices except $Confidence_{ac \to ta}(X \to Y)$and *Mean of deal value* are below average values. Typical M&A transaction rules belonging to cluster 4 are 2911 (petroleum refining) → 2911 (petroleum refining), 1021 (copper ores) → 1021 (copper ores).

Cluster 5 consists of 22 M&A transaction rules highlighting high$Support_{ac \to ta}(X \to Y)$, high $Confidence_{ac \to ta}(X \to Y)$, and high *Mean of deal value*. The consequence's characteristic of M&A transaction rules is low *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 5 are 4813 (telephone communications, except radiotelephone) → 4813 (telephone communications, except radiotelephone). 1381 (drilling oil and gas wells) → 1381 (drilling oil and gas wells). 3533 (oil and gas field machinery and equipment) → 3533 (oil and gas field machinery and equipment).

Cluster 6 consists of 6 M&A transaction rules highlighting high $Support_{ac \to ta}(X \to Y)$, high

$Confidence_{ac \to ta}(X \to Y)$, high *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target.* The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target.* Typical M&A transaction rules belonging to cluster 6 are 7372 (prepackaged software) → 7372 (prepackaged software), 6798 (real estate investment trusts) → 6798 (real estate investment trusts), 6798 (real estate investment trusts) → 7011 (hotels and motels).

Cluster 7 consists of 70 M&A transaction rules. The consequence's characteristics of M&A transaction rules are low *The degree of acquirer,* low *The degree of target.* Typical M&A transaction rules belonging to cluster 7 are 2711 (newspapers: publishing, publishing and printing) → 2711 (newspapers: publishing, publishing and printing), 1521 (general contractors-single-family houses) → 1531 (operative builders), 4512 (air transportation, scheduled) → 4512 (air transportation, scheduled).

Cluster 8 consists of 279 M&A transaction rules highlighting low $Support_{ac \to ta}(X \to Y)$ and extremely low *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are low *The degree of acquirer,* low *The degree of target.* The antecedent's characteristics of M&A transaction rules are low *The degree of acquirer,* low *The degree of target.* The consequence's characteristics of M&A transaction rules are low *The degree of acquirer,* low *The degree of target,* and low *The degree of merged-diversity.* Typical M&A transaction rules belonging to cluster 8 are 7361 (employment agencies) → 7361 (employment agencies). 3949 (sporting and athletic goods, not elsewhere classified) → 3949 (sporting and athletic goods, not elsewhere classified). 2051 (bread and other bakery products, except cookies and crackers) → 2051 (bread and other bakery products except cookies and crackers).

Cluster 9 are composed of 17 M&A transaction rules highlighting low $Confidence_{ac \to ta}(X \to Y)$. The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target,* and high *The degree of merged-diversity.* Typical M&A transaction rules belonging to cluster 9 are 3571 (electronic computers) → 7372 (prepackaged software), 6361 (title insurance) → 7372 (prepackaged software), and 7375 (information retrieval service) → 7372 prepackaged software.

Table 12. Structural patterns of M&A in Phase 3 (2009-2016)

Cluster	Characteristics of pattern											Size of cluster
	Antecedent				*Consequence*				$Support_{ac \to ta}$ $(X \to Y)$	$Confidence_{ac \to ta}$ $(X \to Y)$	*Mean of deal value*	
	The degree of acquirer	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*	*The degree of acquirer*	*The degree of target*	*The degree of merge-diversity*	*The degree of merged-diversity*				
1	87.5946	121.8378	280.7568	475.4595	2.1351	1.6216	1.4324	5.8108	0.0014	0.2776	83.0805	37
2	2219.0000	0.0000	95.0000	857.0000	3.0000	0.0000	1.0000	6.6667	0.0230	0.2292	117.6548	3
3	113.7838	176.7027	560.7027	1206.5405	2.3243	2.4865	1.0000	15.6216	0.0019	0.2446	226.1053	37
4	100.9600	117.7600	114.5600	142.4000	1.6800	2.2800	1.5600	2.6000	0.0014	0.3515	707.1226	25
5	74.1000	77.7000	144.7000	170.6000	1.8000	1.7000	1.4000	2.9000	0.0016	0.4081	2403.6625	10
6	41.1000	33.9000	182.2000	225.3000	2.1000	1.2000	1.4000	3.4000	0.0005	0.3288	4934.4542	10
7	26.8844	34.8090	32.6281	48.9296	1.7085	1.1658	1.4020	1.5779	0.0004	0.3465	58.3313	199
8	29.8750	31.3750	47.5000	64.5417	1.5000	1.0417	1.4583	1.8750	0.0004	0.3742	1265.1076	24
9	43.5714	50.2738	49.7619	61.0714	1.6667	1.2381	1.4881	1.5119	0.0006	0.3406	278.5767	84
mean	64.1282	62.9580	115.0699	206.8531	1.7972	1.3963	1.3963	3.3263	0.0009	0.3326	392.1283	
median	24.0000	31.0000	37.0000	49.0000	2.0000	1.0000	1.0000	1.0000	0.0003	0.2857	112.8000	

Cluster 1 consists of 37 M&A transaction rules highlighting low $Confidence_{ac \to ta}(X \to Y)$, low *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are high *The degree of target*. The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target,* and high *The degree of merged-diversity.* Typical M&A transaction rules belonging to cluster 1 are 7999(amusement and recreation services, not elsewhere classified) → 7011 (hotels and motels), 6021 (national commercial banks) → 6021 (national commercial banks), 8731 (commercial physical and biological research) → 2834 (pharmaceutical preparations).

Cluster 2 consists of 3 M&A transaction rules highlighting high $Support_{ac \to ta}(X \to Y)$, low *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are high *The degree of acquirer*, high *The degree of merged-diversity*. The consequence's characteristics of M&A transaction rules are high *The degree of target*, high *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 2 are 6798 (real estate investment trusts) → 7011 (hotels and motels). 6712 (real estate investment trusts) → 6512 (operators of nonresidential buildings). 6798 (real estate investment trusts) → 6513 (operators of apartment buildings).

Cluster 3 consists of 37 M&A transaction rules highlighting low $Confidence_{ac \to ta}(X \to Y)$. The consequence's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target,* high *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 3 are 1311 (crude petroleum and natural gas) → 1311 (crude petroleum and natural gas), 7375 (information retrieval services) → 7372 (prepackaged software), 6519 (lessors of real property, not elsewhere classified) → 6512 (operators of nonresidential buildings).

Cluster 4 consists of 25 M&A transaction rules highlighting high *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are high *The degree of acquirer,* high *The degree of target.* The consequence's characteristics of M&A transaction rules are low *The degree of target*. Typical M&A transaction rules belonging to cluster 4 are 4911 (electric services) → 4911 (electric services), 1389 (oil and gas field services, not elsewhere classified) → 1389 (oil and gas field services, not elsewhere classified), 2992 (lubricating oils and greases) → 2992 (lubricating oils and greases).

Cluster 5 consists of 10 M&A transaction rules highlighting extremely high $Confidence_{ac \to ta}(X \to Y)$, *Mean of deal value*. The consequence's characteristic of M&A transaction rules is low *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 5 are 2834 (pharmaceutical preparations) → 2834 (pharmaceutical preparations), 4931 (electric and other services combined) → 4924 (natural gas distribution), 1021 (copper ores) → 1311 (crude petroleum and natural gas).

Cluster 6 consists of 10 M&A transaction rules highlighting low $Support_{ac \to ta}(X \to Y)$ high *Mean of deal value*. the average value of all the indices except for $Support_{ac \to ta}(X \to Y)$

and *Mean of deal value*. Typical M&A transaction rules belonging to cluster 6 are 5211 (lumber and other building materials dealers) → 5211 (lumber and other building materials dealers). 3612 (power, distribution and specialty transformers) → 3612 (power, distribution and specialty transformers). 4931 (electric and other services combined) → 4931 (electric and other services combined).

Cluster 7 consists of 199 M&A transaction rules highlighting low $Support_{ac \to ta}(X \to Y)$, extremely low *Mean of deal value*. The antecedent's characteristics of M&A transaction rules are low *The degree of acquirer* and low *The degree of target*. The consequence's characteristics of M&A transaction rules are low *The degree of acquirer*, low *The degree of target*, and low *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 7 are 1522 (general contractors-residential buildings, other than single-family) → 1522 (general contractors-residential buildings, other than single-family), 1711 (plumbing, heating and air-conditioning) → 1711 (plumbing, heating and air-conditioning), 7379 (computer related services, not elsewhere classified) → 7379 (computer related services, not elsewhere classified).

Cluster 8 consists of 24 M&A transaction rules highlighting low $Support_{ac \to ta}(X \to Y)$ and high *Mean of deal value*. The antecedent's characteristic of M&A transaction rules is low *The degree of merged-diversity*. The consequence's characteristic of M&A transaction rules is low *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 8 are 6141 (personal credit institutions) → 6141 (personal credit institutions), 3949 (sporting and athletic goods, not elsewhere classified) → 3949 (sporting and athletic goods, not elsewhere classified), 5012 (automobile and other motor vehicles) → 3711 (motor vehicles and passenger car bodies).

Finally, cluster 9 is composed of 84 M&A transaction rules highlighting low $Confidence_{ac \to ta}(X \to Y)$. The antecedent's characteristics of M&A transaction rules are low *The degree of acquirer* and low *The degree of target*. The consequence's characteristics of M&A transaction rules are low *The degree of acquirer*, low *The degree of target*, and low *The degree of merged-diversity*. Typical M&A transaction rules belonging to cluster 9 are 3845 (electromedical and electrotherapeutic apparatus) → 3841 (surgical and medical instruments and apparatus), 1221 (bituminous coal and lignite surface mining) → 1221 (bituminous coal and lignite surface mining), 7374 (computer processing and data preparation and processing services) → 7374 (computer processing and data preparation and processing services).

5. Conclusion

This study has proposed a systematic and exploratory approach to identifying patterns of M&A at the industry level. The proposed approach can provide valuable information on the identification of dynamic and structural patterns of M&A extracted from large-scale reliable and quantitative databases in wide-range of industries or specific industry that users are interested in. In order to this, the modified association rule mining considering direction of M&A transaction was employed to extract significant M&A transaction rules at the industry level, and the M&A transaction relationship network was constructed to measure characteristics of industries based on the concept of in and out degree centrality. Dynamic and structural patterns of M&A are identified using the changes of two indices ($Support_{ac \to ta}(X \to Y)$ and $Confidence_{ac \to ta}(X \to Y)$) and a K-means cluster algorithm respectively. Finally, empirical analysis was conducted to verify the validity of the proposed methodology.

The main contribution and potential utilization of this study are twofold. Firstly, this study theoretically contributes to M&A research by extending the research scope. Existing literatures on M&A has mainly focused on a firm’s technological capabilities based on patent citation analysis for M&A target selection. The proposed approach considers industry information on the basis of historical M&A transaction data for M&A decision support where corporations determine a principal screening or selection criteria. This approach has hardly tried by researchers in the M&A context. To this end, we integrated the various methods in an effective way. Specifically, we developed the modified association rule mining considering the direction of M&A transaction data. This methodology is a useful tool for extracting the significant rules in the data which direction between items is fixed (e.g. M&A transaction, investment, corporate governance). Six quantitative indicators were also developed to assign the characteristics of industries and significant M&A transaction rules to identify the structural patterns of M&A. Our attempt to adopt diverse methods and to develop quantitative indicators will provide a basis for future studies in the field of M&A research. Secondly, from a practical standpoint, Practitioners are able to identify the dynamic and structure patterns of M&A based on a systematic and exploratory approach with visualized materials. Corporations are able to observe and record whole M&A trend to identify which industries are key player in M&A and which industries are strongly connected statistically. To interpret the M&A trend, Practitioners do not need to be supported by domain knowledge. Additionally, the proposed approach considering evolutionary and industry-level aspects enable practitioners to compare easily characteristics of industries over time in the M&A search process.

Despite of its usefulness, this study is subject to certain limitations, which should be complemented by future research. First, the proposed approach did not consider the other factors that could be explain the characteristics of patterns of M&A. If it is possible to integrate the dataset employed in this study with financial, accounting, and technology information, the characteristics of patterns of M&A will be more plentiful. Furthermore, to cultivate a comprehensive decision support system for the whole M&A process, the further research using factors in financial, accounting, and technology should be performed, because this study only focused on the patterns of M&A for M&A decision at the early stage of the M&A search process. Second, we analyzed 71,264 M&A transactions of about 220,000 M&A transaction from 1995 to 2016. This relatively small number is due to the fact that transaction data on disclosed deal values to the public is rare. Trade-offs between fully non-lost data and information were inevitable. Third, the whole process needs to be systemized and automated. These topics would be fruitful areas for future research.

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